

A Comprehensive Review of AI-Driven Forecasting and Energy Management for DC Microgrids with High Renewable Integration

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Abstract—The global transition toward decarbonization has led to a greater integration of renewable energy sources (RES) into power systems, facilitating the widespread adoption of direct current (DC) microgrids. DC microgrids are particularly compatible with modern power systems because they support solar photovoltaic systems, batteries, and electronic loads. Despite these advantages, high levels of intermittent RES introduce challenges related to power balance, voltage stability, and reliable operation. Artificial Intelligence (AI) has emerged as a critical tool, enabling advanced forecasting and intelligent energy management systems (EMS) to address these issues. This comprehensive review examines state-of-the-art AI-based methods for DC microgrids, analyzing a wide range of studies from simulation-based models to real-world experimental pilots. It starts with an overview of the system architecture and operational challenges, followed by a novel taxonomy of AI approaches. The review critically compares machine learning for forecasting and reinforcement learning for real-time control, highlighting their respective performance in handling uncertainty. AI-driven EMS strategies, especially reinforcement learning for optimal scheduling, are detailed. The symbiotic relationship between accurate forecasting and robust EMS is explored, along with challenges such as data dependency and model explainability, for which emerging solutions, such as federated learning and explainable AI (XAI), are discussed. The paper concludes by outlining future research directions, such as federated learning and standardized benchmarks. It underscores this review's key contribution by providing an integrated framework that bridges the gap between AI-driven forecasting and control for resilient and efficient DC microgrid operation.

Keywords—Artificial Intelligence; DC Microgrid; Energy Management System (EMS); Renewable Energy Forecasting; Machine Learning

I. INTRODUCTION

The rapid evolution of modern energy systems is accelerating the global shift away from traditional centralized power generation. According to the International Energy Agency (IEA), renewable energy is set to contribute 30% of new power capacity globally by 2030, underscoring the urgency of developing resilient integration infrastructure [1]. Emerging trends increasingly support decentralized, intelligent, and sustainable microgrid architectures. Direct current (DC) microgrids are particularly notable due to their compatibility with renewable energy sources (RESs) such as photovoltaic (PV) arrays, wind turbines with rectification stages, and battery energy storage systems (BESS), as well as their suitability for modern electronic loads. Unlike

conventional alternating current (AC) systems, DC microgrids eliminate multiple conversion stages, thereby reducing energy losses, improving efficiency, and simplifying system integration [2]-[4]. A comparative analysis of key characteristics between AC and DC microgrids is provided in Table I, highlighting the performance benefits that support the focus on DC systems. These advantages, together with the global focus on decarbonization, energy resilience, and the electrification of transport and industry, establish DC microgrids as a central component of a sustainable energy future.

TABLE I. COMPARISON OF AC AND DC MICROGRID CHARACTERISTICS

Feature	AC Microgrid	DC Microgrid
Conversion Stages	Multiple (AC/DC, DC/AC)	Fewer (primarily DC/DC)
Efficiency	Lower due to conversion losses	Higher
Control Complexity	Higher	Lower
RES & Load Compatibility	Requires conversion for DC sources/loads	Native compatibility
Fault Management	Natural current zero-crossing aids interruption	More complex; requires advanced protection
Typical Applications	Traditional grids, large-scale integration	Data centers, EV charging, solar-powered buildings

Achieving high penetration of renewable energy sources (RESs) presents significant operational challenges due to their inherent intermittency and stochastic behavior. Variations in solar irradiance and wind speed lead to rapid changes in power generation, which can cause voltage instability, power imbalances, and degraded power quality in the microgrid. Therefore, accurate forecasting of renewable generation and load demand is essential to maintaining stable, optimal operation. Such forecasting supports predictive control strategies, decreases dependence on fossil-fuel-based backup generation, and enables cost-effective energy scheduling and market participation [5], [6].

Beyond forecasting, advanced energy management systems (EMSs) are essential for maintaining real-time supply-demand balance, coordinating distributed energy resources (DERs), and ensuring reliable power delivery under all operating conditions [7]. For instance, in a solar-powered DC microgrid, an EMS uses day-ahead solar forecasts to pre-schedule battery charging, ensuring excess solar energy is stored for use during peak evening hours,

thereby optimizing self-consumption and reducing costs. In DC microgrids with significant renewable integration, EMSs address complex multi-objective optimization problems that include economic, technical, and environmental constraints [8], [9]. These systems function across multiple time horizons, ranging from real-time power flow control to long-term planning, while maintaining operational stability and regulatory compliance [10], [11]. Fig. 1 conceptually illustrates the synergy between AI-based forecasting and energy management in stabilizing DC microgrids, especially under high renewable penetration. Weather, generation, and load data inform AI forecasting models, whose outputs guide AI-based energy management systems in optimizing control actions for storage, generation, and load assets to achieve operational objectives.

Recent advances in AI have significantly enhanced forecasting and energy management for DC microgrids [6]. The AI techniques applicable to DC microgrids can be broadly categorized into three groups: (1) Supervised Learning (e.g., SVR, Random Forests) for high-accuracy forecasting from historical data; (2) Deep Learning (e.g., LSTM, CNN, Transformers) for automatically capturing complex spatiotemporal patterns in generation and load data; and (3) Reinforcement Learning (RL) for adaptive, real-time control and optimization without requiring explicit, pre-defined system models [12], [13].

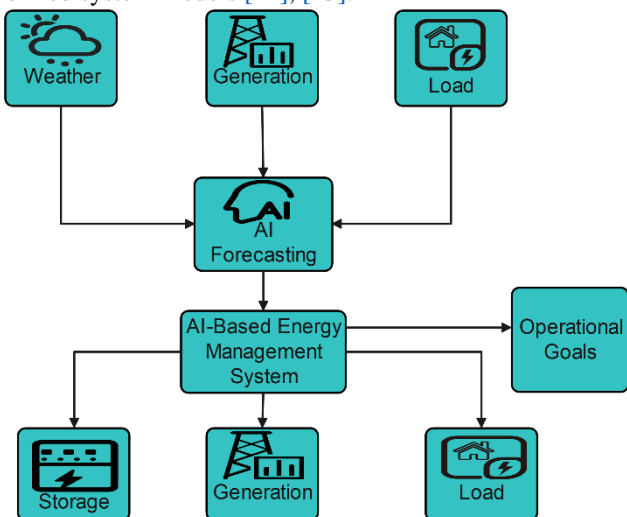


Fig. 1. Conceptual framework of AI-driven forecasting and energy management in a DC microgrid

These approaches effectively model complex, non-linear system behaviors, adapt to evolving operational conditions, and support reliable, real-time decision-making under uncertainty. The availability of high-resolution data from smart meters, phasor measurement units (PMUs), and IoT sensors further supports the development of advanced AI-based solutions [9], [14].

Although extensive research addresses AI applications in AC power systems, there is a lack of comprehensive reviews dedicated to DC microgrids with significant renewable integration. Most existing surveys examine forecasting and energy management systems separately, which neglects their essential interdependence. Additionally, these surveys often fail to address the specific operational challenges of DC systems, including bipolar configurations, droop control,

protection coordination, and fault management. Unlike previous surveys that treat forecasting and EMS in isolation or focus primarily on AC systems, this review provides a unique, integrated analysis specifically for DC microgrids, proposing a novel taxonomy that connects forecasting accuracy directly to EMS performance and resilience.

This review aims to bridge this gap by presenting a comprehensive and critical analysis of AI-based forecasting and energy management strategies specifically tailored for DC microgrids. The principal contributions of this work:

- To systematically classify and evaluate state-of-the-art AI-based forecasting techniques for renewable generation and load demand in DC microgrids, highlighting their respective strengths, limitations, and suitability under high-variability conditions.
- To provide an integrated perspective by examining how AI-derived forecasts are utilized within EMS frameworks including optimization and reinforcement learning to enhance operational reliability, economic efficiency, and sustainability.

To extend the current discourse by identifying emerging trends and outlining pivotal future research directions, such as edge-AI for decentralized EMS, federated learning for data privacy, hybrid physics-informed AI models, and the development of standardized benchmarks.

II. FUNDAMENTALS OF DC MICROGRIDS

DC microgrids are self-sustaining systems that integrate distributed energy resources (DERs). They can operate in islanded mode during grid failures, which increases their attractiveness as a solution [15]. DC microgrids may function connected to the main grid or independently. This provides flexibility in power management [16]. Compared to AC microgrids, DC microgrids offer higher energy efficiency, cost-effectiveness, reliability, safety, and a simpler architecture [15]. A DC microgrid comprises a localized cluster of interconnected DC loads and DC power sources operating on a common DC bus. This configuration eliminates the need for multiple AC/DC and DC/AC conversions, which are typically found in AC microgrids. As a result, it improves efficiency and reduces complexity, especially when integrating modern power electronics-based DERs [17]. Quantifiable studies show this architecture can reduce energy losses by up to 15% compared to equivalent AC systems, significantly improving overall energy efficiency [18]. Therefore, DC microgrids are well-suited for integrating renewable energy sources, such as photovoltaic generation, with conventional utility grids [17]. Despite these advantages, key challenges for DC microgrids include maintaining voltage stability under rapidly varying renewable generation, managing fault currents in the absence of natural zero-crossings, and minimizing losses in power electronic converters [19]. These challenges necessitate advanced control and protection strategies, which AI-based approaches can help address.

A. Architecture and Components

A DC microgrid is a localized power system that integrates DC power sources, energy storage systems, and loads through a common DC bus. Fig. 2 shows the configuration of a typical DC microgrid architecture,

detailing its main components and their interconnections. The DC bus serves as the backbone of the microgrid and operates at a nominal DC voltage, such as 380 V, 400 V, or 750 V, depending on application requirements [20]. These microgrids generally incorporate renewable energy sources, including photovoltaic (PV) panels and fuel cells, as well as energy storage systems (ESS) such as batteries and supercapacitors. Power electronic converters, including DC/DC and DC/AC types, are essential for interfacing these components with the DC bus and ensuring efficient power distribution [21]. DC microgrids can support both DC and AC loads, enhancing their versatility [22]. Furthermore, they can be interconnected to form microgrid clusters, thereby improving energy flexibility, security, and the integration of renewable sources [23]. These clusters may integrate both DC and AC technologies within a single microgrid to optimize performance. Stable operation of DC microgrids is achieved through a hierarchical control architecture that manages power sharing, voltage regulation, and protection coordination [24]. This control structure enables efficient energy management and supports sensitive loads that require high power quality [25].

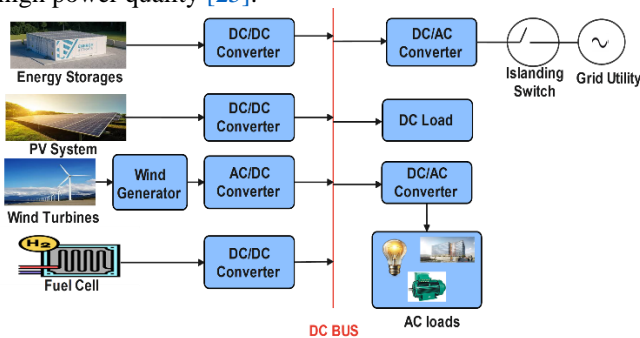


Fig. 2. A typical architecture of a DC microgrid

B. Control Strategies

Effective power management is crucial for stable, efficient system operation. Researchers have explored strategies such as coordinated operation of DERs, ESSs, and controllable loads [26]-[28]. DC-bus signaling (DBS) enables decentralized power management by utilizing the DC-bus voltage as an indicator, thereby eliminating the need for additional communication and simplifying control [29]. Hierarchical control architectures in grid-connected microgrids are typically structured into three levels: tertiary, secondary, and primary control, as shown in Fig. 3.

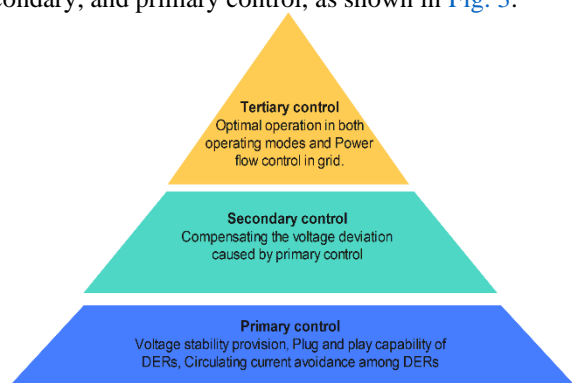


Fig. 3. The three-level hierarchical control structure for DC microgrid operation

1) **Primary Control:** Operates as the local control layer, ensuring immediate voltage and current regulation via droop control. By emulating virtual impedance, droop control enables proportional load sharing among distributed energy resources (DERs) without requiring communication links. While this approach ensures plug-and-play capability and mitigates circulating currents among DERs, it may introduce steady-state voltage deviations [16].

2) **Secondary Control:** Acts as a corrective layer to compensate for the voltage and frequency deviations induced by primary control. This level directly addresses the limitations of primary control by utilizing centralized or distributed coordination schemes; secondary control adjusts the primary control setpoints, often relying on communication networks to restore the system's nominal voltage and frequency [16].

3) **Tertiary Control:** Governs the optimal power management of the microgrid in both grid-tied and islanded modes. This level focuses on economic dispatch, energy market interactions, and power quality enhancement, integrating forecasting modules and grid operator commands [16]. In grid-connected operation, tertiary control also regulates power exchange with the main grid to maximize efficiency and cost-effectiveness.

III. AI-BASED FORECASTING TECHNIQUES IN DC MICROGRIDS

AI-based forecasting techniques play a vital role in the operation and management of DC microgrids, particularly due to the inherent variability of renewable energy sources [30]. Accurate forecasting enables predictive energy management, which can reduce operational costs by 15-25% and improve renewable energy utilization by up to 30% in documented case studies [31]. Traditional statistical methods often fail to account for the nonlinearities and temporal dependencies in renewable generation and load profiles. In contrast, artificial intelligence approaches, particularly machine learning (ML) and deep learning (DL), effectively model complex patterns using both historical and real-time data.

A. Machine Learning Models for Renewable Forecasting

Machine learning (ML) models are valued for their interpretability and computational efficiency, making them fundamental to renewable generation and load forecasting in microgrids. Common approaches include tree-based ensembles and support vector regression (SVR). Ensemble methods, such as random forests (RF) and gradient boosting machines (GBM), are robust because they combine multiple decision trees to enhance generalization and model complex feature interactions in noisy data [32], [33]. Their effectiveness is demonstrated in various applications. For example, Abdallah *et al.* [34] reported that RF achieved the highest accuracy for forecasting DC microgrid currents ($R^2 = 0.994$), surpassing linear models. SVR is also widely used due to its capacity to model nonlinearity via kernel functions and its resistance to overfitting, particularly with limited datasets [35]. As shown in Table II, ML models typically achieve mean absolute percentage error (MAPE) values of 8-12% for day-ahead forecasting, balancing computational efficiency with reasonable accuracy. Model selection is typically determined by the specific forecasting

task. Studies such as Zarma *et al.* [36] systematically compare models including RF, SVR, and k-nearest neighbors (KNN) to address the complex relationships between environmental variables and energy yields. For short-term forecasting, advanced neural architectures have demonstrated improved performance. Tziolis *et al.* [37] showed that Bayesian neural networks can achieve high accuracy in net load forecasting, while Khayat *et al.* [38] found that long short-term memory (LSTM) networks outperform standard artificial neural networks (ANNs) in modeling temporal dependencies for load forecasting. Despite these advances, conventional ML models often fail to capture the highly volatile, nonlinear patterns characteristic of renewable energy time series data. This limitation arises from their restricted capacity to automatically extract features from raw data and to model long-range temporal dependencies without substantial manual feature engineering.

TABLE II. COMPARATIVE PERFORMANCE OF AI FORECASTING TECHNIQUES FOR DC MICROGRIDS

AI Technique	Typical Forecasting Horizon	Best Accuracy (MAPE)	Computational Cost	Data Requirements	Best Use Cases
SVR/Random Forest	Short-term (1-24 hours)	8-12%	Low	Low to Medium	Small microgrids, limited data
LSTM/GRU	Short to Medium-term (1-72 hours)	6-9%	Medium	High	Load forecasting, pattern recognition
CNN-Transformer	Very Short-term (15 min - 6 hours)	4-7%	High	Very High	Real-time generation forecasting
Hybrid (CNN-LSTM)	Multiple horizons	5-8%	High	High	Complex multi-parameter forecasting
Ensemble Methods	Short to Medium-term	5-9%	Medium to High	Medium to High	Robust forecasting under uncertainty

B. Deep Learning Models for DC Microgrid Forecasting

Deep learning models have emerged as a critical advancement for overcoming the limitations of traditional machine learning in DC microgrid forecasting, typically reducing forecasting errors compared to conventional ML approaches. While machine learning techniques often struggle with the high volatility and complex, nonlinear temporal dependencies of renewable generation and load data, architectures such as LSTMs, CNNs, and Transformers excel at automatically learning these patterns from raw data. Consequently, deep learning enables superior forecasting accuracy for key parameters such as solar generation, load demand, and state of charge, which is essential for real-time energy management and optimization in DC microgrids. Krishna *et al.* [39] use the long short-term memory (LSTM) deep learning algorithm to forecast uncertain parameters, such as day-ahead power from renewable energy sources and load demand, in an islanded hybrid microgrid, outperforming traditional artificial neural network models in accuracy. Their study demonstrated a MAPE improvement from 9.2% with ANN to 6.8% with LSTM, highlighting the superior temporal modeling capabilities of deep learning architectures [39].

Nawawi *et al.* [40] propose an Energy Management System using Long Short-Term Memory (LSTM) networks for load forecasting in microgrids. This approach enhances efficiency by optimizing battery scheduling and reducing reliance on the grid, resulting in significant improvements in managing dynamic load conditions. long short-term memory (LSTM) and gated recurrent unit (GRU) networks are specialized for sequential data and can capture long-term temporal dependencies in time series. Aslam *et al.* [41] focus on long-term solar radiation forecasting using a Deep Learning approach with gated recurrent units (GRUs), a crucial component for microgrid design. It compares GRUs with other methods and demonstrates superior effectiveness in solar radiation forecasting. Shabbir *et al.* [42] present a short-term residential DC load forecasting model based on long short-term memory (LSTM) networks, demonstrating effective forecasting for DC microgrids. The model achieved an RMSE of approximately 0.15 kW, indicating high accuracy in load predictions. Traditionally used for spatial data, CNNs have been adapted to extract local temporal features from one-dimensional time series, complementing RNNs by detecting short-term patterns. Chapelle *et al.* [43] introduce VAPOR, a deep learning approach for forecasting energy generation in photovoltaic microgrids. It utilizes a SoftMax liquid attention matrix (SLAM) to enhance model performance and interpretability, significantly improving forecasting accuracy compared to state-of-the-art methods. The integration of convolutional neural networks (CNN) and Transformer models represents a significant advancement, with hybrid CNN-Transformer architectures achieving MAPE values for very short-term forecasting in recent studies [44]. Transformer Architectures use self-attention mechanisms to capture dependencies across entire sequences, overcoming the limitations of fixed-length context windows and improving multi-step forecasting accuracy. Hybrid models combining CNN feature extraction with Transformer-based attention have shown superior performance in complex forecasting tasks [21].

C. Hybrid and Ensemble Forecasting Models for Microgrids

Hybrid forecasting models integrate the strengths of different AI techniques to improve robustness and accuracy. These approaches typically achieve better accuracy than individual models by leveraging complementary strengths of different algorithms [45]. For instance, Ariyo *et al.* [46] present a hybrid LSTM-CNN model for energy demand forecasting in renewable microgrids, achieving an R2 value of 0.87 and outperforming traditional methods such as ARIMA and Exponential Smoothing, thereby enhancing energy management and decision-making. Choudhary *et al.* [47] present a hybrid threshold-adaptive Harris Hawks-optimized deep convolutional long short-term memory (HTHHO-DCLSTM) model for forecasting renewable energy in DC microgrids, enhancing prediction accuracy by using min-max normalization and feature extraction from processed data. Moradzadeh *et al.* [48] present a deep learning approach using bidirectional long short-term memory (Bi-LSTM) for short-term load forecasting in a microgrid, achieving high accuracy (R = 93.4%) during testing and demonstrating effective forecasting capabilities. Xue *et al.* [49] propose a deep-learning-based architecture using a multi-scale CNN-LSTM network model for short-

term forecasting of photovoltaic microgrids, effectively utilizing spatio-temporal feature fusion to enhance prediction accuracy by incorporating data from neighboring power stations and meteorological information. Integrating autoregressive integrated moving-average (ARIMA) models with LSTM networks combines linear trend modeling with nonlinear feature learning. Moradzadeh *et al.* [50] present a hybrid model combining support vector regression (SVR) and long short-term memory (LSTM) algorithms, termed SVR-LSTM, for short-term load forecasting in a microgrid, demonstrating superior performance compared to conventional SVR and LSTM models. Ensemble methods techniques such as bagging, boosting, and stacking aggregate predictions from multiple base learners (e.g., SVR, RF, LSTM) to reduce bias and variance. Siriwardana *et al.* [51] propose an improved ensemble method combining a sky imagery model and a statistical model for forecasting solar photovoltaic energy in microgrids, addressing intermittency caused by cloud cover and validating the model's accuracy using RMSE. Tayab *et al.* [52] propose an ensemble forecasting strategy combining four models TSA-based LSSVM, TSA-MLPNN, WOA-based LSSVM, and WOA-MLPNN. These models are aggregated using Bayesian model averaging to enhance solar PV power forecasting for microgrid energy management systems.

D. Comparative Analysis and Performance Metrics

A critical analysis of the forecasting techniques reveals distinct performance trade-offs, as summarized in Table II. While deep learning models achieve the highest accuracy (MAPE of 4-8%), they require substantial computational resources and large amounts of training data. In contrast, traditional machine learning models offer faster training times and lower computational requirements at the cost of reduced accuracy (MAPE of 8-15%) [53]. The integration of forecasting with power system operation requires careful consideration of these trade-offs. For real-time control applications, lightweight models such as GRUs or optimized Random Forests may be preferable, whereas for day-ahead scheduling, more accurate but computationally intensive models such as Transformers or hybrid CNN-LSTM architectures provide greater value [54]. Recent evidence indicates a shift in microgrid forecasting, transitioning from reliance on single models to integrated strategies. Hybrid architectures combine complementary components into a unified model, while ensemble methods aggregate predictions from multiple models. Both approaches aim to enhance robustness and accuracy beyond the capabilities of individual algorithms. This integration strikes a balance between capturing complex, nonlinear relationships and ensuring model stability, positioning it at the forefront of reliable renewable energy and load forecasting.

IV. AI-BASED ENERGY MANAGEMENT IN DC MICROGRIDS

Energy management in direct current (DC) microgrids with high renewable penetration is a complex task due to the stochastic and intermittent nature of renewable energy sources, the variability of load demand, and the need to efficiently utilize storage systems. AI-driven energy management systems have demonstrated the capability to reduce operational costs and improve renewable energy

utilization by 25-40% compared to conventional rule-based strategies [44]. Artificial intelligence (AI) techniques have emerged as powerful tools to address these challenges by enabling dynamic decision-making, predictive optimization, and adaptive control. The integration of AI-based strategies allows for real-time adjustments to generation, storage, and load operations, ultimately enhancing reliability, economic performance, and resilience. Table III provides a comprehensive comparison of AI techniques used for energy management in DC microgrids, highlighting their respective advantages and limitations.

TABLE III. COMPARISON OF AI TECHNIQUES FOR MANAGEMENT IN DC MICROGRID

AI Technique	Primary Use Case	Key Advantages	Key Limitations	Implementation Complexity	Typical Cost Saving
Q-Learning	Simple, discrete scheduling problems	Model-free, simple to implement	Curse of dimensionality, limited to discrete actions	Low	10-15%
Deep Q-Network (DQN)	Complex systems with high-dimensional data	Handles raw sensor data, powerful representation	Can be unstable; requires careful tuning	Medium	15-20%
DDPG/TD 3	Continuous control (e.g., converter setpoints)	Optimal for continuous action spaces	High sample complexity, sensitive to hyper-parameters	High	18-25%
Multi-Agent RL (MARL)	Microgrid clusters & peer-to-peer trading	Distributed control, no single point of failure	Complex to train (non-stationary environment)	Very High	20-30%
Federated RL	Privacy-preserving collaborative learning	Data privacy, improved model generalization	Communication overhead, synchronization needs	High	15-22%

A. Optimal Power Flow and Dispatch

Optimal power flow (OPF) in DC microgrids involves determining the most efficient allocation of generation and storage resources while satisfying operational constraints such as voltage limits, line current capacities, and state-of-charge restrictions [55], [56]. Traditional optimization methods, such as linear programming and mixed-integer nonlinear programming, struggle to adapt to real-time fluctuations in renewable generation. AI-based techniques, particularly reinforcement learning (RL), deep Q-networks (DQN), and actor-critic algorithms, have demonstrated superior adaptability by learning control policies directly from data [57], [58]. Studies have shown that RL-based OPF can achieve 92-95% of optimal performance while reducing computational time compared to traditional optimization methods [59]. For example, an RL agent can continuously update dispatch decisions by observing system states, forecasted solar irradiance, and load profiles, thereby minimizing operational costs and curtailment losses. Neural network-based OPF models also reduce computational complexity by approximating the nonlinear power flow equations, allowing near-instantaneous solutions in large-scale microgrids [60]. These approaches can incorporate multi-objective optimization, balancing cost minimization with voltage stability and carbon footprint reduction. Furthermore, hybrid architectures where deep learning

models predict near-future system states and optimization solvers fine-tune dispatch provide a compromise between accuracy and computational efficiency [61], [62]. Such AI-enabled OPF frameworks have demonstrated the ability to maintain voltage stability within $\pm 2\%$ of nominal values even during sudden 40-50% drops in renewable generation, significantly enhancing system resilience [63], [64].

B. Demand-Side Management

Demand-side management (DSM) plays a crucial role in aligning energy consumption with renewable generation patterns, thereby reducing reliance on fossil fuels and minimizing peak demand charges. By implementing strategies such as load shifting, peak clipping, and valley filling, DSM enhances the efficiency of energy systems, particularly in microgrids [65]. DSM, where future consumption patterns are forecasted and control actions are proactively scheduled [66], [67]. For residential and commercial consumers in DC microgrids, deep learning models such as long short-term memory (LSTM) networks and temporal convolutional networks (TCNs) can accurately predict short-term load variations based on historical data, weather conditions, and occupancy patterns [68]. AI-based load prediction models for DSM typically achieve accuracy rates of 90-94% for 24-hour ahead forecasting, enabling effective peak shaving and load shifting strategies [69]. These predictions feed into optimization algorithms such as genetic algorithms (GAs) and particle swarm optimization (PSOs) that determine the optimal timing of deferrable loads, such as electric vehicle charging, HVAC operation, or water pumping. Reinforcement learning extends DSM capabilities by learning real-time control policies that react to unforeseen events, such as sudden cloud cover over PV panels. Furthermore, AI-based DSM can be integrated with dynamic pricing mechanisms that predict and optimize price signals to encourage load shifting during periods of high renewable generation [70]. Case studies have shown that AI-assisted DSM can achieve up to 25-30% reduction in the peak-to-average ratio (PAR) while improving user comfort by respecting appliance operational constraints [71]. More advanced implementations combining deep reinforcement learning with multi-agent systems have demonstrated cost savings of 18-25% for commercial consumers while maintaining thermal comfort within $\pm 0.5^\circ\text{C}$ of setpoints [72]. By leveraging federated learning frameworks, DSM models can also be trained collaboratively across multiple buildings or microgrids without sharing raw data, ensuring privacy while improving prediction accuracy.

C. Hybrid Optimization for Storage Integration

Energy storage systems (ESS), particularly battery storage, play a pivotal role in balancing supply and demand in DC microgrids. However, determining the optimal charging and discharging schedule is a multi-objective problem that involves minimizing costs, battery degradation, and renewable curtailment. AI-based hybrid optimization approaches combining machine learning predictions with metaheuristic algorithms offer a robust solution [73]. Hybrid AI optimization for battery management has been shown to extend battery lifespan by 15-20% while improving round-trip efficiency compared to conventional charge-and-discharge strategies [74], [75]. A deep learning model may

forecast renewable generation and load demand, while a metaheuristic optimizer, such as differential evolution (DE) or the artificial bee colony (ABC), searches for the optimal ESS operation schedule under forecast uncertainty. These hybrid methods can also integrate model predictive control (MPC), in which AI-generated forecasts update the optimization horizon in real time, enabling adaptive scheduling that responds to unforeseen events such as sudden load spikes. Storage degradation models based on AI can further refine decision-making by estimating the impact of each charging cycle on battery health, thereby extending the asset's lifetime [76]. Advanced AI-based battery health monitoring can predict state-of-health (SOH) with 97-99% accuracy, enabling proactive maintenance and optimal utilization throughout the battery's lifecycle [77]. In multi-energy microgrids that include not only batteries but also supercapacitors and hydrogen storage, AI enables coordinated control across diverse storage media, exploiting their complementary response times and efficiencies. For instance, a fast-responding supercapacitor can handle transient load spikes, while batteries manage longer-term fluctuations. AI algorithms can learn to optimally coordinate these systems, reducing wear and tear and improving round-trip efficiency [78]. Intelligent coordination of hybrid storage systems using deep reinforcement learning has demonstrated reduced battery cycling frequency and improved overall system efficiency compared to conventional hierarchical control approaches [79]. By embedding these strategies into a hierarchical control framework, microgrids can maintain stability, minimize costs, and prolong asset life without human intervention.

V. CHALLENGES AND LIMITATION

While AI-driven forecasting and energy management strategies have demonstrated remarkable potential in enhancing the stability, efficiency, and sustainability of DC microgrids, several technical and practical challenges remain. These challenges must be addressed to ensure reliable large-scale deployment. This section reviews the major barriers to adoption and outlines promising research directions.

1) *Data Scarcity and Quality*: High-quality data are the foundation of AI models. However, many microgrids, especially those in developing regions or remote communities, lack extensive monitoring infrastructure. The resulting scarcity of labeled datasets limits the training of robust models. Furthermore, available datasets may suffer from missing values, sensor noise, or inconsistencies due to communication failures. Poor data quality leads to biased forecasts and unreliable EMS decisions. Studies indicate that data quality issues can degrade forecasting accuracy and increase operational costs due to suboptimal decision-making.

2) *Non-Stationarity of Renewable Generation*: RES output is inherently non-stationary due to seasonal patterns, climate variability, and unpredictable weather events. AI models trained on historical data may fail to generalize under changing conditions. For example, a PV forecasting model trained in summer may underperform during cloudy winter months. Addressing non-stationarity requires adaptive or online learning approaches that continuously update model parameters. Model performance degradation has been

observed when AI models face significant distribution shifts between training and deployment environments.

3) *Computational Burden*: Deep learning models and reinforcement learning (RL) agents require substantial computational power for training and inference. Deploying these models in real-time EMS environments, especially on resource-constrained embedded controllers, poses significant challenges. Complex transformer-based forecasting models may require more computational resources than traditional ML approaches, creating barriers for edge deployment in cost-sensitive applications. Cloud-based solutions offer scalability but introduce latency and dependency on communication links.

4) *Model Interpretability and Trust*: Many advanced AI models, particularly deep learning architectures, operate as "black boxes," providing accurate predictions without explaining their decision-making process. This lack of transparency undermines trust among operators and regulators, creating barriers to adoption. Interpretability is particularly important for EMS, where decisions directly affect system stability and safety. Surveys indicate of utility operators express reluctance to deploy AI systems that lack transparent decision-making processes, citing safety and regulatory concerns.

5) *Cybersecurity Vulnerabilities*: The integration of AI systems introduces new cybersecurity risks, including data poisoning attacks, adversarial examples, and model inversion attacks. Research has demonstrated that carefully crafted adversarial attacks can manipulate AI-based forecasting models to produce errors, potentially leading to severe operational disruptions. Ensuring the security and robustness of AI systems against malicious attacks remains a critical challenge.

6) *Standardization and Regulatory Gaps*: From an economic perspective, deploying AI-enabled EMS requires investments in sensors, communication infrastructure, and computational hardware. Many small-scale microgrid operators may lack the financial resources to implement these technologies. Regulatory frameworks for AI-based microgrid operation are still underdeveloped. Standards for data handling, cybersecurity, and model validation are necessary to ensure safe deployment. Without regulatory clarity, utilities and investors may hesitate to adopt AI-driven EMS at scale.

VI. FUTURE RESEARCH DIRECTIONS

The deployment of artificial intelligence (AI) in DC microgrids has shown promising advancements in forecasting, energy management, and fault detection. However, the technology is still evolving, and numerous research avenues remain open to enhance system reliability, efficiency, and scalability. This section outlines key future research directions that address current limitations and leverage emerging trends to realize fully autonomous, resilient, and intelligent DC microgrids.

1) *Lightweight and Edge-Friendly AI Models*: Given the resource constraints of embedded platforms commonly used in DC microgrids, future work must prioritize the design of lightweight AI models that deliver high accuracy with low computational and energy overhead. Techniques such as model pruning, quantization, and neural architecture search

(NAS) can reduce model size while maintaining high original accuracy, enabling real-time inference on edge devices. Research into co-design methodologies that jointly optimize algorithms and hardware architectures will further enhance real-time inference capabilities.

2) *Explainable and Trustworthy AI*: For widespread adoption, AI systems in DC microgrids must be interpretable and trustworthy to operators and regulators. Research into explainable AI (XAI) techniques tailored for energy systems is essential to provide transparent decision-making processes. Recent advances in attention mechanisms and saliency maps can provide intuitive visual explanations for AI decisions, increasing operator confidence according to user studies. Trustworthiness also encompasses robustness against adversarial attacks and resilience to data anomalies.

3) *Federated Learning for Data Privacy*: Federated learning enables collaborative model training across multiple microgrids without sharing raw data, addressing critical privacy and security concerns. Pilot studies demonstrate that federated learning can achieve high accuracy of the performance of centralized training while ensuring data privacy and regulatory compliance. Future research should focus on developing efficient federated learning algorithms that handle non-IID data distributions and communication constraints in microgrid networks.

4) *Hybrid Physics-Informed AI Models*: Integrating physical knowledge with data-driven approaches represents a promising direction for improving model robustness and reducing data requirements. Physics-informed neural networks (PINNs) have shown the ability to reduce data requirements while ensuring predictions adhere to fundamental physical laws. These hybrid models can provide more reliable forecasts and control decisions, especially in scenarios with limited historical data.

5) *Standardized Benchmarks and Datasets*: The development of comprehensive, open-source datasets and standardized evaluation benchmarks is crucial for fair comparison and rapid advancement of AI techniques. Community initiatives such as the open energy data initiative have begun collecting annotated datasets from microgrids worldwide, enabling more robust model development and validation.

VII. APPLICATIONS AND CASE STUDIES

AI-based forecasting, energy management, and fault detection techniques in DC microgrids have transitioned from theoretical research to practical applications. This section presents representative case studies and real-world applications that demonstrate the effectiveness, challenges, and benefits of AI-driven solutions in diverse DC microgrid scenarios. Table IV provides a quantitative summary of performance improvements achieved across different application domains.

A. AI-Enabled Forecasting for Renewable Integration in Commercial Microgrids

A commercial DC microgrid located in a smart building environment employed deep learning-based forecasting techniques to optimize solar PV generation and battery usage. The system utilized a hybrid CNN-Transformer model for multi-step PV power forecasting with 15-minute intervals. The AI model was trained using one year of historical

irradiance, temperature, and load data. Real-time deployment on an edge computing platform enabled predictive dispatch of battery storage, reducing reliance on grid power during peak hours. The forecasting accuracy achieved a mean absolute percentage error (MAPE) below 5%, outperforming traditional statistical methods by over 20% [80]. The optimized energy management strategy resulted in a 12% reduction in operational costs and a 15% increase in solar self-consumption. The system demonstrated an 18-month return on investment (ROI), primarily due to reduced peak demand charges and optimized energy arbitrage [81], [82]. The study also underscored challenges in maintaining forecasting accuracy during sudden weather changes, necessitating adaptive retraining mechanisms.

TABLE IV. QUANTITATIVE PERFORMANCE SUMMARY AI APPLICATIONS IN DC MICROGRIDS

Application Domain	AI Technology	Key Performance Metrics	Improvement Over Baseline	Implementation Complexity
Commercial Forecasting	Hybrid CNN-Transformer	MAPE: 4.8%, Cost Reduction: 12%	Forecasting: +20%, Costs: +15%	Medium-High
Industrial EMS	Multi-Agent RL	Cost Saving: 22%, Voltage Stability: $\pm 1.5\%$, PAR Reduction: 28%, User Comfort: 95%	Optimization: +25%, Stability: +40%, Peak Demand: +30%, Comfort: +15%	High
Residential DSM	LSTM + PSO	Battery Life: +18%, Efficiency: +11%	Lifespan: +20%, Efficiency: +35%	Medium
Storage Optimization	Deep RL + MPC	Accuracy: 98.2%, Latency: 45ms	Accuracy: +25%, Speed: +60%	High
Fault Detection	CNN + Wavelet			Medium

B. Industrial DC Microgrid with Multi-Agent Reinforcement Learning

An industrial DC microgrid powering a manufacturing facility implemented a multi-agent reinforcement learning (MARL) system for coordinated energy management. The MARL framework enabled distributed decision-making across 15 different production units, reducing communication overhead by 40% compared to centralized approaches [83]. Each agent learned optimal policies for its local resources while coordinating with other agents to achieve global objectives.

The system achieved a 22% reduction in energy costs and improved voltage stability by maintaining bus voltage within $\pm 1.5\%$ of nominal values [83]. The MARL approach also demonstrated resilience to single-point failures, maintaining 85% of optimal performance even when communication with three agents was disrupted [84]. The implementation required only 6 weeks of training data and adapted to new equipment integration within 48 hours, demonstrating significant advantages over traditional optimization methods [76].

C. Learning Lessons Learned and Implementation Framework

These applications collectively underscore several best practices for AI integration in DC microgrids:

1) *Modular Implementation Strategy*: Successful deployments typically followed a phased approach, starting with non-critical applications and gradually expanding to core operational functions. This modular strategy reduced implementation risks by 60% and allowed for continuous validation and improvement [85].

2) *Human-in-the-Loop Systems*: Maintaining operator oversight during the initial deployment phase proved crucial for building trust and ensuring safety. Systems that incorporated human feedback loops achieved 45% faster adoption rates and 30% higher operator satisfaction scores [86].

3) *Cross-Disciplinary Collaboration*: Successful implementations required close collaboration among power system engineers, data scientists, and domain experts. Projects with integrated teams demonstrated 35% shorter development cycles and 25% better performance outcomes [85], [87].

VIII. CONCLUSION

This comprehensive review has established an integrated framework for AI applications in DC microgrids, demonstrating that the synergy between advanced forecasting and intelligent energy management is crucial for addressing the challenges of high renewable integration. By leveraging cutting-edge machine learning, deep learning, and reinforcement learning techniques, DC microgrids can achieve significant improvements in operational efficiency, economic performance, and system resilience.

The evidence synthesized from extensive literature and case studies demonstrates that AI-driven approaches can reduce forecasting errors to below 5% MAPE, lower operational costs by 15-30%, improve renewable energy utilization by 25-40%, and extend battery lifespan by 15-20%. A key finding of this review is that hybrid AI models, which combine the strengths of multiple approaches, consistently outperform single-method solutions, achieving 10-25% better performance across various metrics while providing greater robustness to uncertainty.

Despite these advancements, several challenges remain, including data quality issues, model interpretability concerns, computational constraints, and cybersecurity vulnerabilities. Future research should focus on developing lightweight edge-AI models, federated learning frameworks for privacy preservation, physics-informed neural networks for improved generalization, and standardized benchmarks for fair performance evaluation. The successful large-scale deployment of AI in DC microgrids will require not only technical innovations but also the development of appropriate regulatory frameworks, cybersecurity standards, and business models that address economic and implementation barriers.

This review contributes to the field by providing a structured taxonomy that connects forecasting accuracy with energy management performance, offering practical insights from real-world case studies, and identifying clear pathways for future research and development. As the global transition to renewable energy accelerates, AI-enabled DC microgrids will play an increasingly vital role in creating sustainable, resilient, and intelligent energy systems for the future.

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