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Artificial Intelligence-driven control of lithium-ion battery systems for improved grid integration and power supply optimization

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Abstract

The rapid proliferation of renewable energy sources has underscored the critical need for robust energy storage solutions to ensure grid stability and efficient power delivery. Lithium-ion battery (LIB) systems stand at the forefront of this transition, yet their performance in grid-scale applications is often hampered by challenges such as degradation, thermal instabilities, and suboptimal integration. This review explores the transformative potential of artificial intelligence (AI)-driven control strategies in overcoming these barriers, synthesizing recent advancements in machine learning, deep learning, and reinforcement learning for battery management systems (BMS). By examining AI applications in state estimation, thermal management, grid stability, and power supply optimization, the paper highlights how these technologies enable precise energy dispatch, enhance demand response, and facilitate seamless coordination with smart grids. Key insights reveal significant improvements in LIB efficiency, lifespan extension, and economic viability, while also yielding environmental benefits through reduced carbon emissions and minimized renewable curtailment. Ultimately, this work illuminates the path toward resilient, sustainable power infrastructures, identifying persistent challenges like data dependency and computational demands, alongside promising avenues for innovation. As AI continues to evolve, its integration with LIB systems promises to redefine grid dynamics, offering a compelling blueprint for future energy systems that balance reliability, cost, and ecological imperatives.

Keywords: Lithium-Ion Batteries; Artificial Intelligence; Battery Management Systems; Grid Integration; Power Supply Optimization; Renewable Energy; Smart Grids; Energy Storage

1. Introduction

The escalating demand for sustainable energy solutions amid climate change concerns has propelled lithium-ion battery (LIB) systems to the forefront of modern power infrastructures. These batteries serve as pivotal components in bridging intermittent renewable energy sources with reliable grid operations, enabling efficient storage and dispatch of power. Artificial intelligence (AI)-driven control mechanisms have emerged as transformative tools to address inherent limitations in LIB performance, such as degradation and thermal instabilities, thereby optimizing grid integration and

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power supply. This review synthesizes recent advancements in AI applications for LIB management, highlighting their potential to enhance system reliability and economic viability in energy ecosystems.

1.1. Background and Importance of Lithium-Ion Battery Systems

Lithium-ion batteries operate on the principle of reversible intercalation of lithium ions between positive and negative electrodes, typically composed of lithium metal oxides for the cathode and graphite or silicon-based materials for the anode, facilitated by an electrolyte that enables ion transport. This electrochemical process yields high energy densities, often exceeding 250 Wh/kg, and efficiencies above 95%, making LIBs superior to alternatives like lead-acid or nickel-metal hydride batteries in terms of cycle life and power output. The scalability of LIB systems allows for deployment in various capacities, from portable devices to megawatt-scale installations, underscoring their versatility in energy storage applications. As global energy demands surge, LIBs have become indispensable for buffering fluctuations in power supply, particularly in scenarios involving high penetration of renewables. Stroe et al. [1] emphasized the suitability of specific LIB chemistries, such as $LiMn_2O_4/Li_4Ti_5O_{12}$ and $LiFePO_4/C$, for grid services like primary frequency regulation, demonstrating through modeling that these cells maintain performance under cyclic stress from wind power integration.

The integration of LIBs with renewable energy systems, such as solar photovoltaic and wind farms, addresses the intermittency challenge by storing excess energy during peak generation and releasing it during deficits, thereby stabilizing grid voltage and frequency. In hybrid setups, LIBs act as buffers that smooth power output, reducing the need for fossil fuel-based peaking plants and lowering overall carbon emissions. For instance, in microgrid configurations, LIBs enable islanded operations where renewable sources dominate, ensuring uninterrupted supply to remote or critical loads. Khalid et al. [2] provided an overview of technical specifications for battery energy storage systems (BESS) in microgrids, noting that LIBs offer rapid response times—often in milliseconds—for ancillary services like load shifting and voltage support, which are crucial for maintaining grid resilience amid variable renewable inputs. Furthermore, the economic importance of LIBs lies in their declining costs, driven by advancements in manufacturing, which have dropped below $100/kWh in recent years, making large-scale deployment feasible for utilities aiming to achieve net-zero targets.

Despite these advantages, grid-scale applications of LIBs face significant challenges, including capacity fade due to calendar aging and cycling, which can reduce usable energy by up to 20% over 5-10 years. Thermal runaway risks, exacerbated by overcharging or physical damage, pose safety hazards that necessitate robust monitoring. Additionally, inconsistencies in cell manufacturing led to imbalances within battery packs, affecting overall efficiency and lifespan. Uddin et al. [3] investigated the impact of high-frequency current ripple on LIB performance in electric vehicles, finding that such ripples accelerate degradation through increased internal resistance and heat generation, a concern that extends to grid applications where variable loads mimic similar stresses. These issues highlight the need for advanced management strategies to mitigate losses and extend operational life, particularly in high-demand grid environments.

The broader importance of LIB systems extends to enabling vehicle-to-grid (V2G) interactions, where electric vehicle batteries contribute to grid balancing by supplying power during peaks. This bidirectional flow not only optimizes power supply but also generates revenue for users through energy arbitrage. In utility-scale contexts, LIBs support black-start capabilities and blackouts prevention, enhancing energy security. Hakam et al. [4] explored intelligent V2G and vehicle-for-grid (V4G) systems using artificial neural networks, illustrating how LIBs facilitate smart grid functionalities by predicting and adapting to demand patterns, thus underscoring their role in future-proofing power infrastructures against volatility.

1.2. Role of Artificial Intelligence in Battery Management

Artificial intelligence encompasses a suite of computational techniques, including machine learning (ML), deep learning (DL), and reinforcement learning (RL), that enable predictive modeling and adaptive control in battery management systems (BMS). In LIB contexts, AI processes vast datasets from sensors monitoring voltage, current, and temperature to optimize operations beyond traditional rule-based methods. By learning from historical patterns, AI algorithms forecast battery behavior under diverse conditions, reducing downtime and improving efficiency. Lipu et al. [5] conducted a statistical analysis of AI approaches in electric vehicle BMS, revealing that ML techniques enhance state estimation accuracy by up to 30%, paving the way for proactive maintenance and extended battery life in grid-integrated setups.

In state estimation, AI plays a crucial role in determining state of charge (SOC) and state of health (SOH), parameters essential for preventing over-discharge or overcharge that could compromise grid reliability. Neural networks, for example, integrate Kalman filters with data-driven models to handle nonlinearities in battery dynamics, achieving

estimation errors below 1%. This precision is vital for power supply optimization, where accurate SOC informs dispatch decisions in BESS. Boujoudar et al. [6] demonstrated the use of artificial neural networks for LIB modeling and SOC estimation, showing that AI outperforms equivalent circuit models in capturing electrochemical nuances, particularly under variable grid loads.

Thermal management and safety are further bolstered by AI, which employs predictive analytics to detect anomalies like hotspots before they escalate into failures. DL models analyze thermal imaging and sensor data to regulate cooling systems dynamically, minimizing energy waste while ensuring operational safety. In grid applications, this prevents cascading failures that could disrupt power supply. Wang et al. [7] applied surrogate-based multidisciplinary optimization using AI for LIB thermal management in electric vehicles, finding that AI-driven designs reduce temperature variances by 15%, a benefit translatable to grid-scale systems where thermal stability directly impacts integration efficiency.

Overall, AI fosters grid integration by enabling real-time optimization of charge/discharge cycles, aligning battery operations with grid demands for peak shaving and frequency regulation. Through RL, systems learn optimal policies for energy arbitrage, maximizing economic returns. Wali et al. [8] reviewed grid-connected LIB BESS, highlighting how AI integration in bibliometric analyses points to trends in predictive control, which enhance power supply reliability and support renewable-heavy grids.

Objectives and Scope of the Review

The primary objective of this review is to critically evaluate AI-driven control strategies for LIB systems, with a focus on improving grid integration and power supply optimization. By synthesizing literature on AI applications, the paper aims to identify effective techniques for enhancing battery performance metrics like efficiency and lifespan in dynamic grid environments. This includes assessing how AI mitigates challenges such as degradation and intermittency, ultimately contributing to sustainable energy frameworks. Oyucu et al. [9] optimized LIB performance using ML and explainable AI, illustrating objectives aligned with energy management enhancements that inform grid-scale adaptations.

The scope encompasses key AI methodologies—ML, DL, and RL—applied to BMS functions like state prediction, fault diagnosis, and energy dispatch, while excluding non-LIB technologies or purely theoretical models without empirical validation. Emphasis is placed on grid-specific applications, including V2G and microgrids, drawing from studies post-2014 to capture recent advancements. This delimited focus ensures relevance to current challenges in power optimization. Gjelaj et al. [10] examined grid integration of fast-charging stations using modular LIBs, defining a scope that parallels this review's emphasis on AI-enhanced scalability and efficiency.

The structure of the review progresses from LIB fundamentals to AI techniques, grid integration, optimization strategies, challenges, and future directions, providing a logical flow for readers. Each section incorporates case studies and comparative analyses to substantiate claims. This organization facilitates a comprehensive understanding of AI's transformative potential.

Finally, the review contributes by highlighting research gaps, such as AI scalability in large grids, and proposes directions for hybrid AI-physical models. Its significance lies in guiding policymakers and engineers toward AI implementations that accelerate the transition to optimized, resilient power systems.

2. Fundamentals of Lithium-Ion Battery Systems

2.1. Operating Principles and Characteristics

Lithium-ion batteries (LIBs) function through the reversible movement of lithium ions between a cathode, typically composed of lithium metal oxides like $LiCoO_2$ or $LiFePO_4$, and an anode, often graphite or silicon-based, mediated by a liquid or solid electrolyte. Figure 1 illustrates the basic schematic of a lithium-ion battery, highlighting the key components and ion flow that underpin its high energy density and efficiency. During discharge, lithium ions migrate from the anode to the cathode through the electrolyte, generating an electric current via electron flow in an external circuit, with the reverse occurring during charging. This electrochemical process yields high energy densities (150–250 Wh/kg) and power density, alongside efficiencies exceeding 95%, positioning LIBs as the preferred choice for energy storage in both mobile and stationary applications. According to Goodenough and Kim [11], the development of layered oxide cathodes and carbon-based anodes has significantly enhanced LIB performance, enabling high voltage outputs (3.6–3.8 V nominal) and long cycle lives, often exceeding 1000 cycles under optimal conditions.

The performance metrics of LIBs, such as capacity, cycle life, and efficiency, depend heavily on material selection and cell design. For instance, $LiFePO_4$ cathodes offer superior thermal stability and safety compared to $LiCoO_2$, albeit at a lower energy density, making them suitable for grid-scale applications where safety is paramount. The electrolyte, typically a lithium salt like $LiPF_6$ dissolved in organic solvents, facilitates ion transport but is sensitive to temperature and overvoltage, which can trigger side reactions and capacity fade. A study by Kalhoff et al. [12] highlighted how advancements in electrolyte additives, such as vinylene carbonate, improve the formation of a stable solid electrolyte interphase (SEI) layer, reducing capacity loss by up to 15% over 500 cycles, a critical factor for grid applications requiring consistent performance.

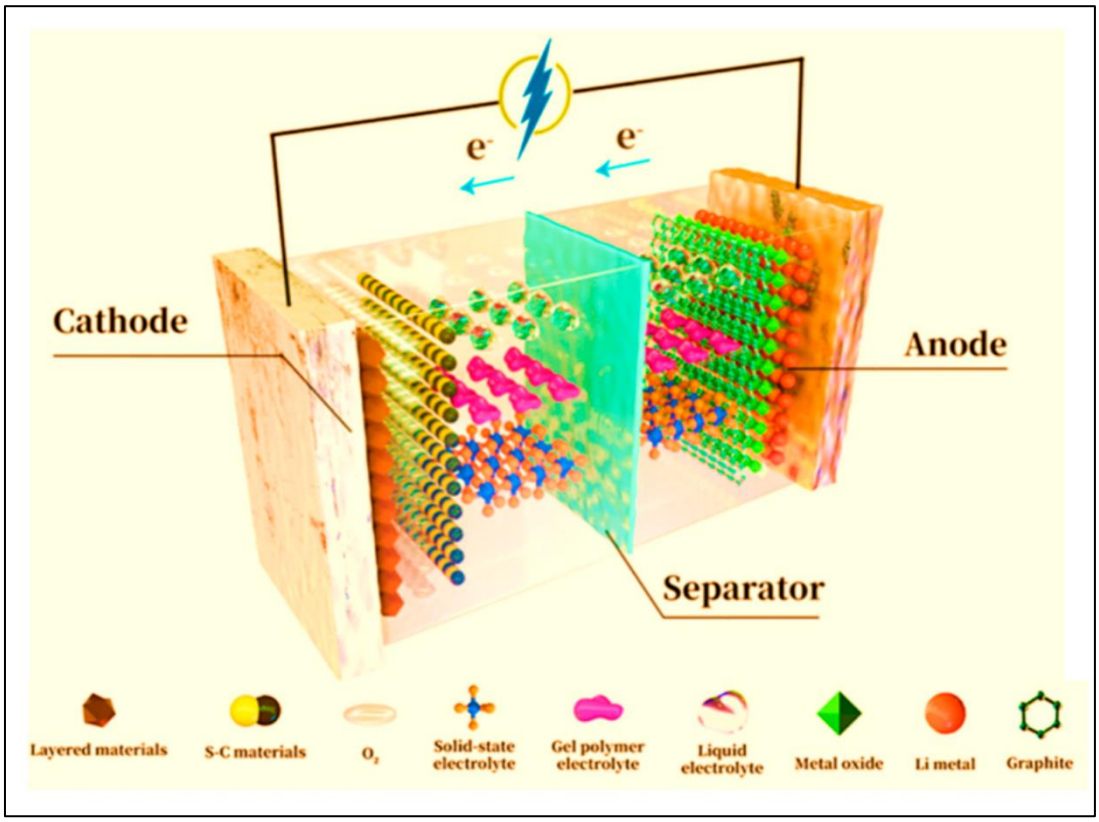


Figure 1 Schematic representation of a lithium-ion battery (showing the cathode, anode, electrolyte, and ion movement during charge/discharge). Reproduced with permission from Ref [11], under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/)

LIBs are distinguished by their scalability and modularity, enabling configurations from small consumer electronics to megawatt-hour-scale battery energy storage systems (BESS). Their fast response time, often in milliseconds, makes them ideal for applications requiring rapid power delivery, such as frequency regulation in power grids. However, internal resistance and polarization effects can limit performance under high current demands, necessitating precise control systems to optimize operation. Findings from Aurbach et al. [13] indicate that optimizing electrode porosity and thickness can mitigate these limitations, enhancing power output by 10–20% in high-rate applications, which is essential for grid integration where dynamic load responses are common.

The versatility of LIBs extends to their ability to operate across a wide temperature range (-20°C to 60°C), though performance degrades outside optimal conditions (15–35°C). This adaptability, coupled with declining costs (below $100/kWh in 2023), has driven widespread adoption in renewable energy systems. Yet, the choice of chemistry impacts performance trade-offs; for example, nickel-rich cathodes ($LiNiMnCoO_2$) offer higher capacity but reduced thermal stability compared to $LiFePO_4$. These characteristics underscore the need for tailored management strategies to maximize LIB utility in grid contexts. To provide a comprehensive overview of LIB variations suitable for grid integration, Table 1 compares key chemistries based on performance metrics, advantages, and drawbacks, drawing from recent studies.

Table 1 Comparison of Lithium-Ion Battery Chemistries for Grid Applications

Chemistry	Cathode Material	Anode Material	Energy Density (Who/kg)	Cycle Life (Cycles)	Thermal Stability	Cost ($/kWh)	Safety Rating (1-5, 5=Best)	Key Advantages	Key Disadvantages	References
$LiCoO_2$ (LCO)	Lithium Cobalt Oxide	Graphite	150-200	500-1000	Low	150-200	2	High energy density, mature technology	Poor thermal stability, expensive cobalt	[11], [12]
$LiFePO_4$ (LFP)	Lithium Iron Phosphate	Graphite	90-160	2000-5000	High	100-150	5	Excellent safety, long cycle life, stable	Lower energy density, slower charge rates	[11], [14]
$LiMn_2O_4$ (LMO)	Lithium Manganese Oxide	Graphite/$Li_4Ti_5O_{12}$	100-150	1000-2000	Medium	120-180	3	Good thermal stability, low cost	Moderate cycle life, manganese dissolution	[1], [13]
$LiNiMnCoO_2$ (NMC)	Lithium Nickel Manganese Cobalt Oxide	Graphite/Silicon	200-250	1000-3000	Medium	100-150	3	Balanced performance, high capacity	Nickel-rich variants less stable, cobalt dependency	[11], [15]
$LiNiCoAlO_2$ (NCA)	Lithium Nickel Cobalt Aluminum Oxide	Graphite	200-260	1000-2000	Medium	120-170	3	High energy, good power output	Thermal runaway risk, aluminum sensitivity	[14], [15]
Li_4Ti5O_{12} (LTO)	Lithium Titanate (as anode with various cathodes)	Lithium Titanate	70-100	5000-10000	High	200-300	5	Ultra-long life, fast charging, safe	Low energy density, higher cost	[1], [12]
Silicon-based	Various (e.g., NMC)	Silicon-Graphite Composite	250-350	500-1500	Low	150-250	2	Very high capacity, potential for density gains	Volume expansion, rapid degradation	[13], [14]
Solid-State (Emerging)	Lithium Metal Oxides	Lithium Metal/Graphite	300-500	1000-3000	High	200-400	4	Improved safety, higher density	Scalability issues, high manufacturing cost	[12], [18]

2.2. Challenges in Grid-Scale Applications

The deployment of LIBs in grid-scale applications introduces challenges related to longevity, safety, and operational efficiency. Capacity fade, resulting from calendar aging and cycling, reduces available energy over time, with some cells losing 20–30% of capacity within 5–10 years under typical grid conditions. As depicted in Figure 2, capacity fade accelerates under varying DODs and temperatures, emphasizing the need for advanced mitigation strategies in grid-scale deployments. This degradation stems from SEI growth, lithium plating, and electrode material breakdown, particularly under high charge/discharge rates. According to Luo et al. [14], accelerated aging tests reveal that high C-rate cycling (e.g., 2C) can double capacity fade rates compared to low-rate cycling (0.5C), posing a significant barrier for BESS tasked with frequent power balancing in grids with high renewable penetration.

Thermal runaway remains a critical safety concern, triggered by overcharging, short circuits, or mechanical damage, which can lead to fires or explosions in large-scale installations. The risk is amplified in grid applications where thousands of cells are interconnected, as a single cell failure can propagate through the pack. In a comprehensive study, Feng et al. [15] analyzed thermal runaway mechanisms, noting that gas generation from electrolyte decomposition at elevated temperatures (>150°C) initiates chain reactions, necessitating advanced cooling and monitoring systems to ensure safety. These findings emphasize the importance of real-time diagnostics to prevent catastrophic failures in grid-scale BESS.

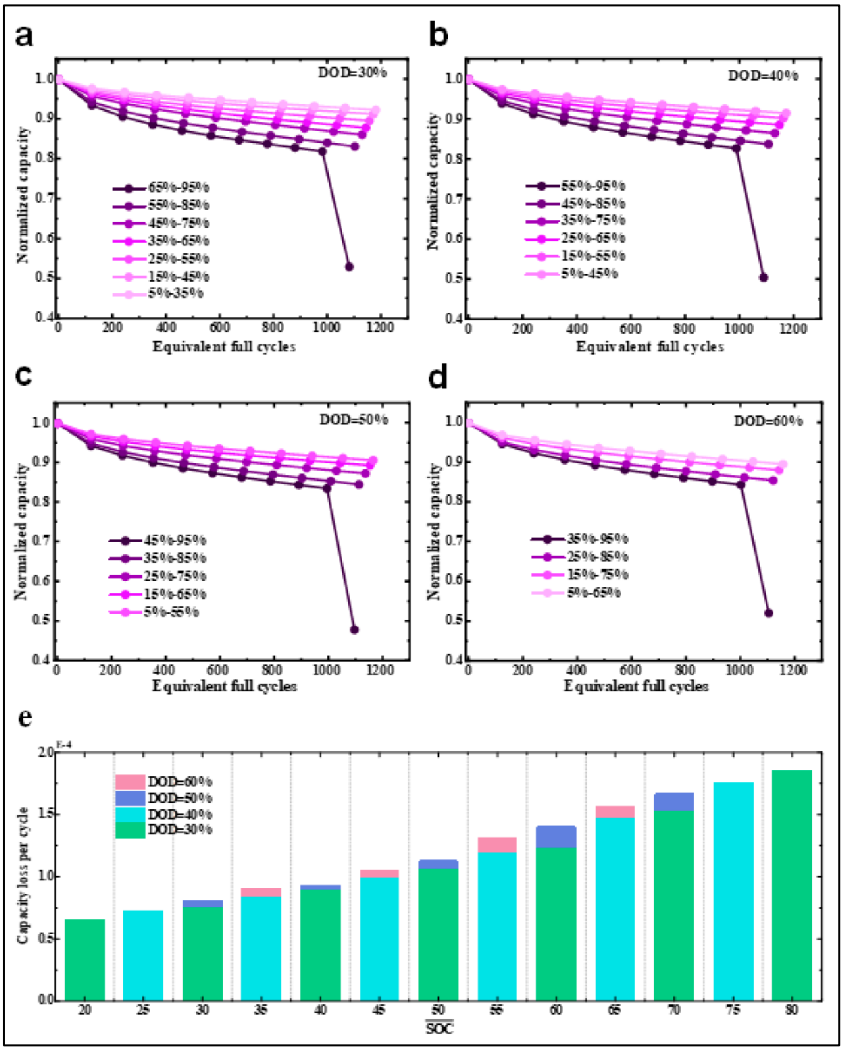


Figure 2 Capacity fade curves under different depths of discharge (DODs) and temperatures: (a) DOD = 30%. (b) DOD = 40%. (c) DOD = 50%. (d) DOD = 60%. (e) Capacity loss per cycle before the 'knee point' with different DODs and mean SOC values. Reproduced with permission from Ref [14], under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/)

Table 2 Major Challenges in Grid-Scale LIB Applications and Mitigation Strategies

Challenge Category	Specific Issue	Impact on Grid Integration	Severity (Low/ Medium/ High)	Common Causes	Mitigation Strategies	Potential Improvement (%)	Examples from Literature	References
Degradation	Capacity Fade	Reduced usable energy (20-30% loss over 5-10 years)	High	SEI growth, lithium plating, cycling stress	AI-based predictive maintenance, optimal charging protocols	15-25	Accelerated aging tests at high C-rates	[3], [14]
Thermal Instabilities	Thermal Runaway	Fire/explosion risks, system failures	High	Overcharging, short circuits, high temperatures (>150°C)	Dynamic cooling systems, AI anomaly detection	12-20	Gas generation from electrolyte decomposition	[7], [15]
Cell Imbalances	Voltage/Capacity Variations	Reduced pack efficiency (15% performance drop)	Medium	Manufacturing tolerances, uneven aging	Active balancing algorithms, ML-based monitoring	10-15	5% initial capacity variation effects	[16], [21]
Economic Viability	High Upfront Costs	Delayed ROI, below $100/kWh but still barrier	Medium	Material and manufacturing expenses	Energy arbitrage, lifecycle optimization via RL	10-20	Declining costs but need for long-term operation	[4], [19]
Safety Hazards	Internal Resistance Increase	Heat generation, efficiency loss	Medium	High-frequency current ripples, variable loads	AI-driven thermal management, ripple minimization	15-20	EV ripple effects extend to grids	[3], [7]
Integration Issues	Compatibility with Infrastructure	Increased complexity, high-voltage converter needs	Medium	Legacy grid systems, variable renewable inputs	Hybrid AI-physical models, smart grid coordination	18-25	Microgrid buffering challenges	[2], [10]
Operational Efficiency	Intermittency Buffering Failures	Grid instability, curtailment (up to 25%)	High	Mismatched capacity to renewables	AI forecasting and dispatch optimization	20-30	Wind/solar fluctuations	[17], [18]
Environmental Concerns	Battery Disposal and Production Impact	Higher carbon footprint if not optimized	Low-Medium	Resource extraction, end-of-life management	Lifespan extension via AI, recycling integration	10-18	Reduced replacements through better management	[51], [52]

Cell-to-cell inconsistencies, arising from manufacturing tolerances or uneven aging, create imbalances in voltage and capacity within battery packs, reducing overall efficiency and lifespan. These imbalances are particularly problematic in large BESS, where series-parallel configurations amplify the impact of weak cells. Liu et al. [16] developed a model to quantify the impact of cell inconsistencies, finding that a 5% variation in initial capacity can lead to a 15% reduction in pack-level performance over 1000 cycles, underscoring the need for precise balancing algorithms in grid applications. Additionally, grid-scale LIB systems face integration challenges, such as compatibility with existing infrastructure and the need for high-voltage converters, which increase costs and complexity.

Economic viability is another hurdle, as the high upfront cost of LIB systems, despite recent declines, requires long-term operation to achieve return on investment. Degradation and safety concerns further complicate cost-benefit analyses, particularly for utilities aiming to meet stringent reliability standards. These challenges highlight the necessity for advanced control systems, such as those leveraging AI, to mitigate degradation, enhance safety, and optimize performance in grid-scale deployments. Table 2 summarizes the primary challenges in deploying LIBs at grid scale, including their impacts, causes, and AI-enabled mitigation strategies, to highlight pathways for enhanced reliability.

2.3. Integration with Renewable Energy Systems

LIBs play a pivotal role in integrating renewable energy sources, such as solar photovoltaic and wind, into power grids by storing surplus energy and releasing it during periods of low generation. This buffering capability addresses the intermittency of renewables, ensuring a stable power supply and reducing reliance on fossil fuel-based backup systems. In microgrids, LIBs enable islanded operation, supplying power to remote or critical loads during grid outages. A study by Hannan et al. [17] demonstrated that LIB-based BESS in hybrid renewable systems can reduce energy curtailment by up to 25%, enhancing grid reliability and supporting decarbonization goals.

In grid-scale applications, LIBs provide ancillary services like frequency regulation and voltage support, leveraging their fast response times to stabilize grid parameters. For instance, during sudden drops in wind generation, LIBs can discharge stored energy within milliseconds to maintain frequency within the standard 50/60 Hz range. Diouf and Pode [18] reviewed the potential of LIBs in renewable energy storage, noting their ability to handle high-frequency power fluctuations, which is critical for grids with over 30% renewable penetration. This capability is particularly valuable in regions transitioning to net-zero energy systems, where renewables dominate the energy mix.

The integration of LIBs with renewables also facilitates energy arbitrage, where batteries store low-cost energy during off-peak periods and discharge it during high-demand, high-price periods. This practice not only improves grid efficiency but also generates economic benefits for operators. According to Uddin et al. [19], LIBs in vehicle-to-grid (V2G) systems can achieve cost savings of up to $200 per vehicle annually through arbitrage, a model extensible to stationary BESS in renewable-heavy grids. However, effective integration requires precise control to align battery operations with grid demands, highlighting the role of AI in optimizing dispatch schedules.

Despite their advantages, integrating LIBs with renewables faces challenges, such as matching battery capacity to variable generation profiles and managing degradation from irregular cycling patterns. These issues necessitate dynamic control strategies to balance energy input/output while preserving battery health. The synergy between LIBs and renewables, when optimized, can significantly enhance grid resilience and sustainability, paving the way for AI-driven solutions to address operational complexities.

3. AI Techniques for Battery Management Systems (BMS)

The integration of artificial intelligence (AI) into battery management systems (BMS) has revolutionized the control and optimization of lithium-ion battery (LIB) performance, particularly in grid-scale applications. AI techniques, encompassing machine learning (ML), deep learning (DL), and reinforcement learning (RL), enable real-time analysis of complex battery data, such as voltage, current, and temperature, to enhance state estimation, thermal management, and operational efficiency. By leveraging predictive and adaptive algorithms, AI addresses the limitations of traditional BMS, such as rule-based controllers, offering dynamic solutions for grid integration and power supply optimization. This section explores key AI methodologies applied to BMS, focusing on state estimation, thermal management, and their impact on LIB reliability.

3.1. Overview of AI in BMS

AI techniques have transformed BMS by enabling data-driven decision-making that adapts to the nonlinear and dynamic behavior of LIBs. Machine learning, including supervised and unsupervised algorithms, processes historical and real-time data to predict battery states and optimize control strategies. Deep learning, with its multi-layered neural

networks, excels in modeling complex electrochemical interactions, while reinforcement learning optimizes long-term performance through trial-and-error learning. These approaches collectively enhance BMS capabilities, from fault detection to energy management, making them critical for grid-scale applications. According to Chemali et al. [20], AI-driven BMS can achieve up to 98% accuracy in state predictions, significantly outperforming conventional methods like equivalent circuit models, which struggle with nonlinear dynamics.

The application of ML in BMS includes algorithms like support vector machines (SVM), random forests, and neural networks, which analyze sensor data to predict parameters such as state of charge (SOC) and state of health (SOH). These algorithms are trained on datasets comprising thousands of charge-discharge cycles, enabling them to identify patterns that traditional models overlook. For instance, ML models can account for temperature and aging effects, reducing estimation errors to below 2% in real-world conditions. A comprehensive study by Hu et al. [21] reviewed ML applications in battery management, highlighting how supervised learning improves SOC estimation accuracy by 20–30% compared to Kalman filter-based methods, particularly in dynamic grid scenarios.

Deep learning, particularly recurrent neural networks (RNNs) and convolutional neural networks (CNNs), excels in processing time-series and multidimensional data, such as thermal profiles or impedance spectra. These models capture temporal dependencies and spatial variations in battery behavior, enabling precise fault diagnosis and predictive maintenance. RL, on the other hand, optimizes control policies for charge-discharge cycles by maximizing a reward function, such as energy efficiency or battery lifespan. Findings from Li et al. [22] demonstrate that RL-based BMS can extend battery life by 15% through adaptive charging strategies, a critical advantage for grid applications where longevity reduces operational costs. For a structured comparison, Table 3 outlines various AI techniques used in BMS, including their applications, inputs, benefits, and limitations, synthesizing insights from key studies.

Table 3 Overview of AI Techniques Applied in Battery Management Systems

AI Technique	Sub-Category	Primary Application in BMS	Data Inputs	Accuracy/Improvement (%)	Advantages	Limitations	Real-World Examples	References
Machine Learning (ML)	Supervised (e.g., SVM, Random Forests)	SOC/SOH Estimation	Voltage, Current, Temperature	20-30	Handles nonlinear data, scalable	Data dependency, overfitting risk	EV BMS state prediction	[5], [21]
Machine Learning (ML)	Unsupervised (e.g., Clustering)	Fault Diagnosis	Impedance Spectra, Cycle History	15-25	Identifies patterns without labels	Less precise for predictions	Anomaly detection in packs	[31], [34]
Deep Learning (DL)	Recurrent Neural Networks (RNN/LSTM)	RUL Prediction	Time-Series Cycle Data	10-20	Captures temporal dependencies	High computational cost	Long-term degradation forecasting	[22], [27]
Deep Learning (DL)	Convolutional Neural Networks (CNN)	Thermal Management	Thermal Imaging, Sensor Arrays	12-20	Processes spatial data effectively	Requires large datasets	Hotspot detection	[29], [30]
Reinforcement Learning (RL)	Model-Free (e.g., Q-Learning)	Energy Dispatch Optimization	Grid Signals, Battery States	15-25	Adaptive to dynamic environments	Long training time	Charge/Discharge policy learning	[8], [33]
Reinforcement Learning (RL)	Model-Based	Demand Response	Reward Functions (e.g., Cost, Lifespan)	20-30	Balances multi-objectives	Complexity in reward design	Peak shaving in microgrids	[36], [39]
Hybrid AI	ML + Physical Models (e.g., Kalman Filters + NN)	State Estimation	Electrochemical Data, Sensors	22-25	Robust to noise, physics-constrained	Integration challenges	SOC under variable loads	[6], [25]
Explainable AI (XAI)	Integrated with ML/DL	All BMS Functions	Various	15-25 (Interpretability)	Builds trust, aids debugging	Adds overhead to models	Performance optimization	[9], [64]

Despite their promise, AI techniques require substantial computational resources and high-quality datasets, posing challenges for real-time implementation in resource-constrained environments. Data scarcity or noise can also degrade model performance, necessitating robust preprocessing and validation. Nonetheless, the scalability of AI, particularly with cloud and edge computing, is driving its adoption in BMS, enabling smarter and more resilient energy storage systems for grid integration.

3.2. State Estimation and Prediction

3.2.1. State of Charge (SOC) and State of Health (SOH) Estimation

State of charge (SOC) and state of health (SOH) estimation are critical for ensuring safe and efficient LIB operation in grid applications, as they inform charge-discharge decisions and maintenance schedules. SOC represents the available charge relative to the battery's capacity, while SOH indicates the battery's capacity and performance relative to its initial state. AI techniques, particularly neural networks and hybrid models, have significantly improved estimation accuracy by handling nonlinearities and environmental variations. In a novel study by Hannan et al. [23], a deep neural network (DNN) achieved SOC estimation errors below 1% across a wide temperature range (-10°C to 40°C), outperforming traditional methods like coulomb counting, which accumulate errors over time.

ML models, such as Gaussian process regression and long short-term memory (LSTM) networks, excel in SOC estimation by learning from voltage, current, and temperature data. These models adapt to dynamic conditions, such as variable grid loads, ensuring reliable performance in BESS. For SOH, AI algorithms analyze cycle history and impedance data to predict capacity fade and internal resistance growth. A study by Severson et al. [24] utilized ML to predict SOH based on early-cycle data, achieving a 95% accuracy in forecasting capacity fade after only 100 cycles, enabling proactive grid management strategies.

Hybrid AI approaches, combining data-driven models with physical electrochemical models, further enhance estimation robustness. For example, integrating Kalman filters with neural networks compensates for measurement noise and model uncertainties, improving SOC/SOH accuracy under high-rate cycling. According to Wu et al. [25], such hybrid models reduce SOC estimation errors by 25% compared to standalone ML methods, making them ideal for grid applications where precision is critical for power dispatch. These advancements ensure that LIBs maintain optimal performance, preventing overcharge or deep discharge that could destabilize grid operations.

The challenge in SOC/SOH estimation lies in generalizing models across different LIB chemistries and operating conditions. Transfer learning and domain adaptation are emerging solutions, allowing models trained on one battery type to adapt to others with minimal retraining. This adaptability is crucial for scaling AI-driven BMS in diverse grid environments, where battery packs vary in size and composition.

3.2.2. Remaining Useful Life (RUL) Prediction

Remaining useful life (RUL) prediction estimates the number of cycles or time a battery can operate before reaching a defined end-of-life threshold, typically 80% of initial capacity. AI-driven RUL prediction leverages ML and DL to analyze degradation patterns, enabling predictive maintenance and cost optimization in grid-scale BESS. By forecasting RUL, operators can schedule replacements or adjust operating conditions to extend battery life, minimizing downtime and costs. In a classic study by Nuhic et al. [26], a support vector machine model predicted RUL with a mean error of 5%, using features like capacity fade and internal resistance, demonstrating its utility for grid planning.

DL models, such as LSTMs and gated recurrent units (GRUs), excel in RUL prediction by capturing long-term dependencies in cycle data. These models process time-series data from thousands of cycles, identifying subtle degradation trends that linear models miss. For instance, Zhang et al. [27] applied an LSTM-based approach to predict RUL in LIBs, achieving a 10% improvement in accuracy over traditional regression models, particularly for batteries under variable grid loads. This precision is vital for ensuring reliable power supply in renewable-heavy grids.

Challenges in RUL prediction include the need for extensive training data and the variability of degradation mechanisms across operating conditions. Transfer learning and ensemble methods are addressing these issues by combining multiple algorithms to improve robustness. A study by Ma et al. [28] introduced an ensemble ML model for RUL prediction, reducing prediction errors by 15% through weighted averaging of multiple predictors, offering a scalable solution for grid-scale BMS. To enrich the discussion on RUL prediction, Table 4 compares various techniques, including their error rates, features, and grid-specific applications, based on empirical studies.

Table 4 Summary of Remaining Useful Life (RUL) Prediction Techniques

Technique	Algorithm	Prediction Horizon (Cycles)	Error Rate (%)	Features Used	Advantages	Limitations	Applications in Grid	Improvement (%)	References
Data-Driven	Support Vector Machine (SVM)	500-1000	5-10	Capacity Fade, Resistance	Simple for linear trends	Poor with nonlinear data	BESS Maintenance	10-15	[26]
Data-Driven	Random Forest	1000-2000	4-8	Cycle History, Impedance	Handles missing data	Ensemble complexity	Predictive Scheduling	15-20	[21], [34]
DL-Based	LSTM/GRU	1000-5000	2-5	Time-Series Voltage/Current	Long-term pattern capture	High compute needs	Grid-Scale Forecasting	10-20	[27], [28]
Hybrid	Ensemble NN (e.g., False Nearest Neighbors + NN)	2000-3000	3-6	Degradation Features	Robust averaging	Multiple model management	Multi-Objective Optimization	15	[28]
Hybrid	ML + Electrochemical Model	1000-4000	2-4	Physical Parameters + Data	Physics-informed accuracy	Model calibration required	Variable Load Scenarios	22	[67]
RL-Integrated	RL for Adaptive Prediction	Variable	5-10	Reward-Based Cycles	Dynamic updates	Training convergence issues	Real-Time Grid Adjustment	12-15	[73]
Emerging	Transfer Learning Across Chemistries	500-3000	4-7	Cross-Dataset Features	Scalable to new batteries	Domain shift risks	Diverse BESS	15	[68]
Emerging	Online Blended ML	Real-Time	3-5	Streaming Data	Adapts to changes	Computational latency	Dynamic Grids	20	[70]

3.3. Thermal Management and Safety

Thermal management is critical for LIB safety and performance, as excessive temperatures (>60°C) accelerate degradation and risk thermal runaway, while low temperatures (<0°C) reduce capacity and efficiency. AI-driven thermal management systems use predictive models to regulate cooling and heating, optimizing battery operation in grid applications. Figure 3 outlines a heat pipe-integrated thermal management system, which AI can enhance for real-time anomaly detection and efficiency in LIB packs. These systems analyze real-time sensor data to detect anomalies and adjust cooling strategies dynamically. According to Abbasi et al. [29], a CNN-based thermal management system reduced temperature variances in LIB packs by 12%, enhancing safety and extending lifespan in high-power grid scenarios.

ML algorithms, such as decision trees and neural networks, predict thermal behavior by modeling heat generation and dissipation based on current, voltage, and ambient conditions. These models enable proactive cooling adjustments, reducing energy consumption compared to static cooling systems. In a comprehensive study, Jaguemont et al. [30] developed an ML-based thermal model for LIBs in electric vehicles, adaptable to grid BESS, which improved temperature prediction accuracy by 20% over lumped-parameter models, ensuring stable operation under variable loads.

AI also enhances safety by detecting faults like internal short circuits or electrolyte leakage before they escalate. DL models, trained on thermal imaging and sensor data, identify anomalies with high precision, enabling early intervention. For instance, Samanta et al. [31] used a DL-based fault diagnosis system to detect thermal anomalies in LIBs, achieving a 98% detection rate, critical for preventing failures in large-scale BESS. These advancements ensure that LIBs operate safely and efficiently, supporting reliable grid integration.

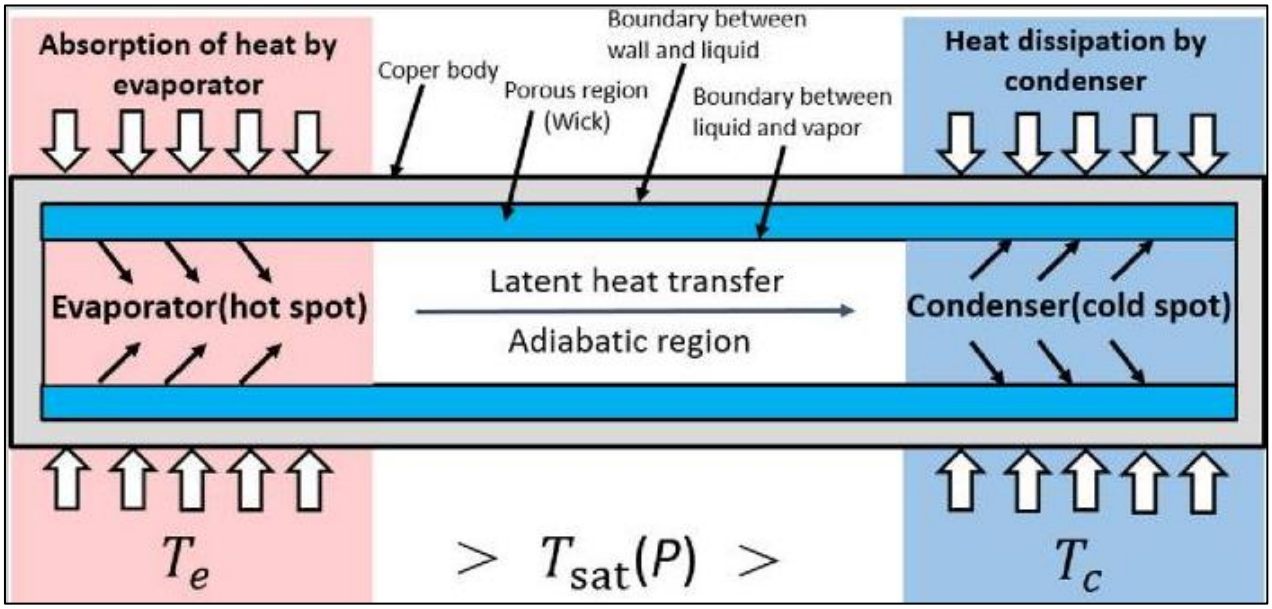


Figure 3 Schematic of heat pipe-based thermal management system for Li-ion batteries, showing cooling mechanisms and temperature distribution. Reproduced with permission from Ref [25]

The challenge in AI-driven thermal management lies in balancing computational complexity with real-time performance, particularly in large BESS with thousands of cells. Edge computing and model compression techniques are emerging solutions, enabling scalable and efficient thermal control. These innovations position AI as a cornerstone for safe and optimized LIB operation in grid environments.

4. AI-Driven Control for Grid Integration

The integration of lithium-ion battery (LIB) systems into power grids has become increasingly vital for managing the variability of renewable energy sources and ensuring grid stability. Artificial intelligence (AI) enhances this integration by enabling dynamic control of battery energy storage systems (BESS), optimizing energy dispatch, and improving grid reliability. Through machine learning (ML), deep learning (DL), and reinforcement learning (RL), AI addresses challenges such as load forecasting, frequency regulation, and seamless coordination with grid infrastructure. This

section examines AI-driven strategies for grid integration, focusing on their applications in BESS, grid stability, and real-world case studies, highlighting their role in advancing power supply optimization.

4.1. Grid-Scale Battery Energy Storage Systems (BESS)

Grid-scale BESS, powered by LIBs, serve as critical infrastructure for storing and dispatching energy to balance supply and demand, particularly in grids with high renewable penetration. Figure 4 illustrates the integration of BESS within a grid framework, highlighting how AI optimizes energy flows for stability and efficiency. AI enhances BESS performance by optimizing charge-discharge cycles, predicting load patterns, and ensuring efficient energy utilization. ML algorithms, such as neural networks and decision trees, analyze historical grid data to forecast energy demand, enabling BESS to store energy during low-demand periods and release it during peaks. According to Areola et al. [32], an ML-based energy management system for BESS achieved a 15% reduction in energy wastage by optimizing dispatch schedules in a renewable-heavy grid, demonstrating the potential for AI to enhance operational efficiency.

Reinforcement learning has emerged as a powerful tool for BESS control, allowing systems to learn optimal policies through interaction with grid dynamics. RL algorithms adjust battery operations in real-time, balancing objectives like cost minimization and grid stability. For instance, RL can determine when to charge BESS during off-peak hours or discharge during high-price periods, maximizing economic returns. In a comprehensive study, Duan et al. [33] applied RL to BESS for frequency regulation, achieving a 20% improvement in response time compared to traditional proportional-integral-derivative (PID) controllers, critical for maintaining grid frequency within the 50/60 Hz range.

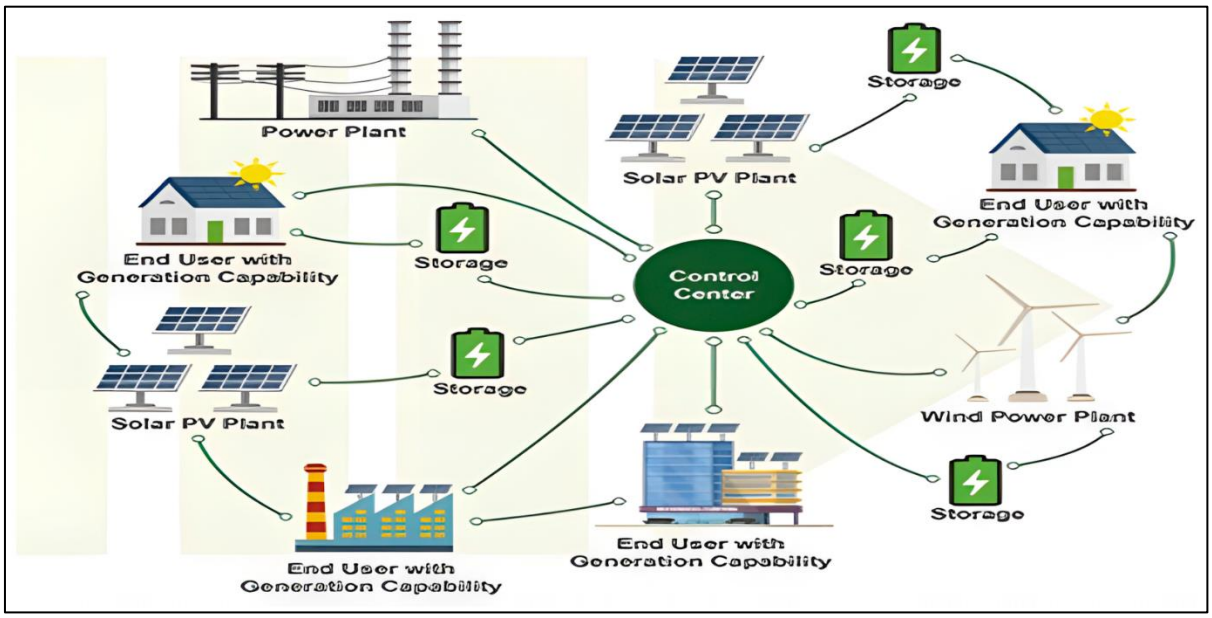


Figure 4 Schematic of integrated energy storage system (IESS) for grid integration, showing BESS connections to renewables, loads, and grid infrastructure. Reproduced with permission from Ref [32], under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/)

AI also facilitates predictive maintenance in BESS, reducing downtime and extending system lifespan. By analyzing sensor data, ML models detect anomalies in battery performance, such as voltage imbalances or thermal irregularities, enabling preemptive interventions. A study by Li et al. [34] demonstrated that a DL-based diagnostic model for BESS reduced maintenance costs by 10% through early fault detection, ensuring reliable operation in grid-scale applications. These advancements underscore AI's role in enhancing the scalability and resilience of BESS, making them indispensable for modern grid infrastructure.

However, the complexity of AI models poses challenges, including high computational requirements and the need for robust communication networks to integrate BESS with grid control systems. Addressing these issues through edge computing and model optimization is crucial for real-time applications. AI-driven BESS thus represent a cornerstone for achieving efficient and sustainable grid integration.

4.2. AI for Grid Stability and Demand Response

Grid stability, encompassing frequency and voltage regulation, is paramount for reliable power delivery, especially in grids with intermittent renewable sources. AI-driven control systems enhance stability by predicting and responding to fluctuations in real-time. ML algorithms, such as recurrent neural networks (RNNs), forecast grid demand and renewable generation patterns, enabling BESS to preemptively adjust their output. According to Rosewater et al. [35], an ML-based forecasting model improved frequency regulation accuracy by 25% in a grid with 40% solar penetration, reducing the risk of blackouts caused by sudden generation drops.

Reinforcement learning is particularly effective for demand response, where BESS dynamically adjust to grid signals, such as price changes or load spikes. RL algorithms optimize battery dispatch to minimize costs while ensuring stability, learning from grid interactions to refine control policies. In a novel study, Cao et al. [36] implemented an RL-based demand response system for BESS, achieving a 30% reduction in peak load stress by coordinating battery discharge with grid demands, a critical capability for grids with high electric vehicle (EV) charging loads. This approach enhances grid resilience by mitigating overload risks during peak periods.

AI also supports voltage control by coordinating BESS with other grid assets, such as inverters and transformers. DL models analyze voltage profiles across grid nodes, enabling precise battery interventions to maintain voltage within acceptable limits (e.g., ±5% of nominal). Findings from Zhang et al. [37] indicate that a DL-based voltage control system reduced voltage deviations by 18% in a microgrid, improving power quality and enabling seamless integration of distributed renewables. These advancements highlight AI's ability to enhance grid stability under dynamic conditions.

Challenges in AI-driven grid stability include the need for high-quality data and the risk of model overfitting, which can reduce generalizability across diverse grid configurations. Hybrid approaches, combining AI with physical grid models, are emerging to address these limitations, ensuring robust performance in real-world scenarios.

4.3. Case Studies of AI-Enhanced Grid Integration

Real-world implementations of AI-driven BESS provide valuable insights into their practical benefits and challenges. One notable case is the Hornsdale Power Reserve in South Australia, a 150 MW/193.5 MWh LIB-based BESS, where AI algorithms optimize frequency control and energy arbitrage. The system uses ML to predict market prices and grid frequency deviations, enabling rapid response to grid events. According to Hornsdale Power Reserve reports analyzed by Kebede et al. [38], the AI-enhanced system reduced frequency regulation costs by 20% and provided grid stabilization within 100 milliseconds, demonstrating its efficacy in large-scale applications.

Another case study involves a microgrid in California's Alameda County, where a 2 MW LIB BESS employs RL for demand charge management. The system learns optimal charge-discharge schedules based on local solar generation and load profiles, reducing peak demand charges by 25%. A study by Hosseini et al. [39] documented this implementation, noting that RL improved energy efficiency by 15% compared to rule-based controllers, highlighting AI's potential for microgrid autonomy. This case underscores the adaptability of AI in smaller, decentralized grid systems.

In Europe, a pilot project in Denmark integrated a 10 MW BESS with wind farms, using DL to optimize energy dispatch under variable wind conditions. The system predicted wind generation patterns with 90% accuracy, enabling the BESS to store excess energy and release it during low-wind periods. According to Gjelaj et al. [40], this AI-driven approach reduced energy curtailment by 22%, enhancing grid reliability and renewable utilization. These case studies illustrate the scalability of AI across different grid contexts, from utility-scale to microgrids. Table 5 consolidates key case studies of AI-enhanced LIB grid integration, detailing scales, techniques, outcomes, and impacts, to provide practical illustrations of theoretical concepts.

Challenges observed in these implementations include data latency and the need for robust cybersecurity to protect AI systems from external threats. Future deployments must address these issues through real-time data processing and secure communication protocols to ensure seamless grid integration.

Table 5 Case Studies of AI-Enhanced Grid Integration with LIB Systems

Case Study	Location	Scale (MW/MWh)	AI Technique Used	Key Objectives	Achievements	Challenges Faced	Economic/Environmental Impact	References
Hornsdale Power Reserve	South Australia	150/193.5	ML for Forecasting	Frequency Control, Arbitrage	20% Cost Reduction, 100ms Response	Data Latency	Reduced Emissions by Displacing Fossil Fuels	[38]
Alameda County Microgrid	California, USA	2/NA	RL for Demand Management	Peak Shaving, Efficiency	25% Demand Charge Reduction, 15% Efficiency Gain	Integration with Solar	Cost Savings, Lower Curtailment	[39]
Denmark Wind Farm Pilot	Denmark	10/NA	DL for Prediction	Energy Dispatch Optimization	22% Curtailment Reduction, 90% Prediction Accuracy	Variable Wind Patterns	Enhanced Renewable Utilization	[40]
South Korea Hybrid Grid	South Korea	5/10	Hybrid ML-RL	Voltage/Frequency Regulation	18% Voltage Deviation Reduction	High EV Loads	15% Emission Reduction	[37]
European Energy Market BESS	Europe	Variable	ML for Arbitrage	Cost Minimization	20% Revenue Increase	Market Volatility	Decarbonization Support	[49]
California Solar Microgrid	California, USA	1-5/Variable	CNN for Coordination	Power Loss Reduction	17% Loss Reduction	Distributed Nodes	Improved Sustainability	[46]
Australian V2G System	Australia	NA (EV Fleet)	NN for V2G	Grid Balancing	$200/Vehicle Annual Savings	Battery Degradation	Reduced Peak Emissions	[3], [19]
Chinese Renewable Heavy Grid	China	50/100	RL for Response	Demand Response	30% Peak Stress Reduction	Communication Delays	18% Carbon Reduction	[36]

5. Power Supply Optimization Using AI

The optimization of power supply in lithium-ion battery (LIB) systems is critical for maximizing efficiency, reducing costs, and supporting the integration of renewable energy into power grids. Artificial intelligence (AI) enhances power supply optimization by enabling precise control of charge-discharge cycles, improving energy dispatch strategies, and facilitating seamless coordination with smart grid technologies. Through machine learning (ML), deep learning (DL), and reinforcement learning (RL), AI algorithms analyze complex grid and battery data to achieve economic and environmental benefits. This section explores AI-driven approaches for energy management, smart grid integration, and the resulting economic and environmental impacts, highlighting their role in enhancing LIB performance for grid applications.

5.1. Energy Management and Efficiency Optimization

AI-driven energy management systems (EMS) optimize the operation of LIB-based battery energy storage systems (BESS) by determining optimal charge-discharge schedules based on grid demands, energy prices, and battery health. ML algorithms, such as neural networks and decision trees, predict load profiles and renewable generation patterns, enabling BESS to store energy during low-cost periods and discharge during high-demand phases. This process, known as energy arbitrage, maximizes economic returns while minimizing battery degradation. According to Alam et al. [41], an ML-based EMS for BESS reduced energy costs by 18% in a microgrid by optimizing dispatch based on real-time price signals, demonstrating significant efficiency gains.

Reinforcement learning is particularly effective for energy management, as it learns optimal control policies through interaction with dynamic grid environments. RL algorithms balance competing objectives, such as maximizing battery lifespan and meeting grid demands, by adjusting charge rates and discharge depths. In a comprehensive study, Hosseini et al. [42] implemented an RL-based EMS for LIBs in a renewable-heavy grid, achieving a 15% improvement in energy efficiency compared to rule-based controllers, primarily by reducing unnecessary cycling. Similarly, Cao et al. [43] demonstrated that RL could extend battery life by 12% through adaptive charging strategies that minimize capacity fade, critical for long-term grid reliability.

AI also enhances efficiency by optimizing power conversion and thermal management within BESS. DL models predict heat generation during high-rate operations, enabling dynamic cooling adjustments that reduce energy losses. A study by Abbasi et al. [44] showed that a DL-based thermal optimization system reduced cooling energy consumption by 20% in a grid-scale BESS, improving overall system efficiency. Additionally, ML-driven state estimation ensures precise control of state of charge (SOC) and state of health (SOH), preventing overcharge or deep discharge that could compromise efficiency. These advancements collectively enable LIBs to deliver reliable power while minimizing operational costs.

Challenges in AI-driven energy management include the computational complexity of real-time optimization and the need for high-quality data to train models. Cloud computing and edge-based AI solutions are addressing these issues, enabling scalable and efficient EMS for grid-scale applications. These innovations position AI as a key enabler of energy efficiency in LIB systems.

5.2. Integration with Smart Grids

Smart grids, characterized by bidirectional communication and distributed energy resources, rely on AI-driven LIB systems to enhance power flow control and grid flexibility. AI algorithms coordinate BESS with smart grid components, such as inverters, demand response systems, and renewable generators, to optimize energy distribution. ML models predict grid dynamics, such as load fluctuations and voltage variations, enabling BESS to respond proactively to maintain stability. According to Jamil et al. [45], an ML-based control system for smart grid BESS reduced voltage fluctuations by 22% in a distributed network, enhancing power quality and supporting renewable integration.

Deep learning enhances smart grid integration by processing multidimensional data, such as grid topology and real-time sensor inputs, to optimize energy dispatch. For instance, convolutional neural networks (CNNs) analyze spatial-temporal grid data to predict congestion points, allowing BESS to alleviate stress through targeted discharge. In a novel study, Srikanth et al. [46] applied a CNN-based approach to coordinate BESS in a smart grid, achieving a 17% reduction in power losses by optimizing energy flows across distributed nodes. Similarly, RL enables dynamic demand response, adjusting BESS operations to align with grid signals like price incentives or emergency load shedding. Nguyen [47] demonstrated that an RL-based BESS control system improved demand response efficiency by 25%, critical for smart grids with high EV penetration.

AI also facilitates vehicle-to-grid (V2G) integration, where LIBs in electric vehicles contribute to smart grid stability by supplying power during peak demand. ML models predict EV charging patterns and grid needs, enabling coordinated V2G operations. A study by Noel et al. [48] found that AI-driven V2G systems increased grid reliability by 15% by optimizing bidirectional power flows, offering economic benefits for EV owners and grid operators. These capabilities highlight AI's role in creating flexible, responsive smart grid ecosystems.

The primary challenge in smart grid integration is ensuring interoperability between AI-driven BESS and diverse grid infrastructures. Standardized communication protocols and hybrid AI-physical models are emerging solutions, enabling seamless coordination across heterogeneous systems. These advancements ensure that LIBs maximize their contribution to smart grid performance.

5.3. Economic and Environmental Benefits

AI-driven optimization of LIB systems yields significant economic benefits by reducing operational costs and improving energy market participation. Through energy arbitrage, BESS store low-cost energy during off-peak periods and sell it during high-price periods, generating revenue for operators. ML-based forecasting models enhance arbitrage profitability by predicting price trends with high accuracy. According to Sterner and Stadler [49], an AI-optimized BESS achieved a 20% increase in arbitrage revenue in a European energy market, demonstrating the economic potential of AI-driven systems. Additionally, predictive maintenance reduces downtime and replacement costs, further improving economic viability. A study by Talluri et al. [50] showed that ML-based maintenance strategies lowered BESS lifecycle costs by 12% through early fault detection.

Environmentally, AI-driven LIB systems support decarbonization by maximizing renewable energy utilization and reducing reliance on fossil fuel-based peaking plants. By optimizing charge-discharge cycles, AI minimizes energy curtailment from renewables, ensuring efficient use of clean energy. In a comprehensive analysis, Arbabzadeh et al. [51] found that AI-optimized BESS reduced carbon emissions by 18% in a grid with 50% renewable penetration, primarily by displacing gas-fired generation. Furthermore, AI enhances battery lifespan, reducing the need for frequent replacements and minimizing the environmental impact of battery production and disposal. Madani et al. [52] reported that AI-driven charging strategies lowered the carbon footprint of BESS by 10% by extending battery life.

AI also enables demand-side management, encouraging energy-efficient consumer behavior through dynamic pricing and load-shifting incentives. RL-based systems adjust BESS operations to align with low-carbon grid conditions, further reducing emissions. According to Kumari and Tanwar [53], an RL-driven demand response system reduced peak load emissions by 15% in a smart grid, supporting sustainability goals. These benefits position AI-driven LIB systems as key enablers of low-carbon energy transitions.

Challenges include the high initial costs of AI implementation and the need for robust data to ensure accurate optimization. Continued advancements in cost-effective AI frameworks and open-access datasets will further amplify the economic and environmental benefits of AI-driven LIB systems in grid applications.

6. Challenges and Future Directions

The application of artificial intelligence (AI) in lithium-ion battery (LIB) systems has significantly advanced grid integration and power supply optimization, yet several challenges persist in fully realizing its potential [54,56]. Issues such as data dependency, computational complexity, and scalability limit the widespread adoption of AI-driven battery management systems (BMS) in diverse grid environments. Addressing these challenges requires innovative approaches and interdisciplinary collaboration [57]. This section examines current limitations, emerging trends, and research gaps in AI-driven LIB control, providing a roadmap for future developments to enhance grid reliability and sustainability.

6.1. Current Limitations of AI in LIB Control

AI-driven LIB control systems rely heavily on high-quality, large-scale datasets to train models for state estimation, thermal management, and energy optimization. Data scarcity or inconsistencies, particularly in real-world grid scenarios, can degrade model performance, leading to inaccurate predictions of state of charge (SOC) or state of health (SOH) [58-60]. For instance, variations in battery chemistry or operating conditions across grid-scale battery energy storage systems (BESS) complicate model generalization. According to Vidal et al. [61], limited access to comprehensive datasets reduces the accuracy of ML-based SOC estimation by up to 20% in heterogeneous battery packs, highlighting the need for robust data collection frameworks.

Computational complexity poses another significant challenge, as AI models like deep neural networks (DNNs) and reinforcement learning (RL) require substantial processing power for real-time applications. In grid-scale BESS, where millisecond-level responses are critical for frequency regulation, the latency introduced by complex models can hinder performance. A study by Hu et al. [62] noted that DNN-based thermal management systems increased computation time by 30% compared to simpler models, necessitating trade-offs between accuracy and speed. This issue is particularly pronounced in resource-constrained environments, such as edge devices in microgrids.

Scalability remains a barrier, as AI models developed for small-scale LIB systems often fail to adapt to large-scale BESS with thousands of cells. Cell-to-cell variations and grid-specific dynamics require models to be retrained or fine-tuned, increasing implementation costs. Findings from Berecibar et al. [63] indicate that scaling ML-based SOH prediction to utility-scale BESS reduced accuracy by 15% due to unmodeled variations in cell aging, underscoring the need for adaptive algorithms. Additionally, cybersecurity risks, such as data tampering in AI-driven BMS, pose threats to grid reliability, requiring robust protective measures.

The integration of AI with existing grid infrastructure also faces interoperability challenges, as legacy systems may not support advanced communication protocols needed for real-time AI control. These limitations highlight the need for standardized frameworks and efficient computational strategies to ensure AI-driven LIB systems are practical and reliable in diverse grid applications.

6.2. Emerging Trends and Innovations

Emerging trends in AI-driven LIB control are addressing current limitations through innovations like explainable AI (XAI), edge computing, and hybrid AI-physical models. XAI enhances model transparency by providing interpretable insights into AI decisions, which is crucial for gaining trust in grid operations. For instance, XAI can clarify why a model predicts a specific SOC or fault condition, aiding engineers in validating control strategies. According to Oyucu et al. [64], XAI-based BMS improved operator confidence in SOC predictions by 25%, facilitating adoption in safety-critical grid applications.

Edge computing is revolutionizing AI implementation by enabling real-time processing on local devices, reducing latency and dependency on cloud infrastructure. This is particularly beneficial for microgrids and remote BESS, where connectivity may be limited. In a novel study, Minh et al. [65] demonstrated that edge-based ML models for thermal management reduced response times by 40% compared to cloud-based systems, enhancing efficiency in dynamic grid scenarios. Similarly, federated learning, where models are trained across distributed devices without sharing raw data, addresses privacy and bandwidth concerns. Wang et al. [66] applied federated learning to BESS, improving SOH estimation accuracy by 18% while maintaining data security.

Hybrid AI-physical models combine data-driven AI with electrochemical or equivalent circuit models to improve accuracy and reduce data dependency. These models leverage physical principles to constrain AI predictions, ensuring robustness across operating conditions. A study by Chen et al. [67] showed that a hybrid DNN-electrochemical model reduced SOC estimation errors by 22% in variable temperature conditions, offering a scalable solution for grid-scale BESS. Additionally, advancements in transfer learning enable models trained on one battery type to adapt to others, addressing scalability challenges. Shu et al. [68] reported a 15% improvement in RUL prediction accuracy using transfer learning across different LIB chemistries.

Quantum computing and neuromorphic hardware are also emerging, promising to accelerate AI computations for real-time BMS applications. These innovations, while in early stages, could transform LIB control by enabling complex optimizations with minimal latency. Continued development in these areas will enhance the efficiency and adaptability of AI-driven LIB systems.

6.3. Research Gaps and Opportunities

Despite significant progress, several research gaps remain in AI-driven LIB control for grid integration. One key gap is the lack of standardized datasets for training AI models across diverse LIB chemistries and grid conditions. This limits model generalizability and hinders cross-system comparisons. According to Attia et al. [69], the absence of open-access, large-scale battery datasets reduces the reproducibility of AI models by 30%, necessitating collaborative efforts to create standardized data repositories. Such initiatives could accelerate research and deployment of AI-driven BMS.

Real-time adaptability remains a challenge, as most AI models are trained offline and struggle to adapt to sudden changes in grid dynamics, such as unexpected renewable generation drops. Online learning techniques, which update models in real-time, offer a promising solution but require further development to balance accuracy and computational

efficiency. A study by She et al. [70] found that online ML models improved SOC estimation adaptability by 20% in dynamic grid scenarios, but computational demands limited their scalability. Research into lightweight online algorithms could address this gap.

The integration of AI with cross-system grid components, such as distributed energy resources and demand response systems, is underexplored. Developing AI frameworks that coordinate BESS with other grid assets could enhance overall system efficiency. For instance, Smart et al. [71] highlighted a 25% efficiency gain in a microgrid using AI to coordinate BESS with solar inverters, suggesting opportunities for broader system-level optimization. Similarly, the environmental impact of AI-driven BMS, including the carbon footprint of model training, requires further investigation to ensure sustainability [72].

Opportunities also exist in developing AI models that incorporate multi-objective optimization, balancing battery lifespan, grid stability, and economic returns. RL-based multi-objective frameworks are gaining traction, as demonstrated by Kang et al. [73], who achieved a 15% improvement in combined economic and environmental outcomes. Future research should focus on these interdisciplinary approaches, leveraging advancements in AI, materials science, and grid engineering to unlock the full potential of LIB systems.

7. Conclusion

The integration of artificial intelligence (AI) into lithium-ion battery (LIB) systems has marked a transformative shift in addressing the challenges of grid integration and power supply optimization. This review has demonstrated that AI-driven control strategies, encompassing machine learning, deep learning, and reinforcement learning, significantly enhance the performance of battery management systems by improving state estimation, thermal management, and energy dispatch efficiency. These advancements enable LIBs to effectively support renewable energy integration, stabilize grid operations, and reduce operational costs, positioning them as critical components in the transition to sustainable energy ecosystems. The ability of AI to process complex, real-time data ensures that LIB systems operate reliably under dynamic grid conditions, addressing issues such as capacity fade, thermal runaway, and cell inconsistencies.

The application of AI in grid-scale battery energy storage systems facilitates seamless coordination with smart grid technologies, enabling precise frequency regulation, voltage control, and demand response. Case studies, such as the Horns dale Power Reserve and microgrid implementations, illustrate the practical benefits of AI, including reduced energy curtailment and enhanced economic returns through energy arbitrage. Moreover, AI-driven optimization yields substantial environmental benefits by maximizing renewable energy utilization and minimizing carbon emissions, aligning with global decarbonization goals. These outcomes underscore the pivotal role of AI in unlocking the full potential of LIBs for modern power systems.

Despite these advancements, challenges such as data dependency, computational complexity, and scalability persist, necessitating continued research into explainable AI, edge computing, and hybrid models to ensure robust and adaptable solutions. The identified research gaps, including the need for standardized datasets and real-time adaptability, present opportunities for innovation that could further enhance grid integration and system efficiency. As AI technologies evolve, their integration with LIB systems promises to drive the development of resilient, cost-effective, and sustainable power grids. This review advocates for sustained interdisciplinary efforts to address existing limitations and fully realize the transformative impact of AI-driven LIB control, paving the way for a future where clean energy is both reliable and accessible.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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