AI-Enhanced Battery Management Systems: A Comprehensive Review of Intelligent Monitoring, Fault Diagnosis, and Optimization Techniques

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Abstract
The increasing deployment of lithium-ion batteries in critical infrastructure like electric vehicles and renewable energy storage necessitates advanced Battery Management Systems (BMS) that ensure operational efficiency, safety, and longevity. Conventional BMS face limitations in handling the nonlinear dynamics and environmental variability inherent to battery behavior. This review examines the application of Artificial Intelligence (AI) and Machine Learning (ML) methodologies to enhance the precision of State of Charge (SoC) and State of Health (SoH) estimations, facilitate early fault diagnosis, optimize thermal regulation, and enable predictive maintenance frameworks. The synergistic integration of Internet of Things (IoT) technologies supports real-time data acquisition and distributed analytics, rendering BMS more intelligent and scalable. Emerging research trends also emphasize AI-based strategies for managing second-life batteries in grid-scale storage applications, promoting sustainability and cost-efficiency. This comprehensive analysis synthesizes recent advancements, underscoring the transformative impact of AI-enhanced BMS architectures on energy management systems.

Keywords: Battery Management system (BMS), Machine Learning (ML), State of Charge (SoC), State of Health (SoH), Artificial Intelligence (AI), Fault Detection, Thermal Management, Internet of Things (IoT), Predictive Modelling

Introduction

Driven by the accelerating shift toward sustainable mobility and renewable energy solutions, the reliance on lithium-ion batteries, with their favorable energy density and cycle life, has become pronounced. These electrochemical systems, however, exhibit complex, time-variant behavior sensitive to multifaceted operational parameters such as thermal conditions, load profiles, and voltage fluctuations, which necessitate sophisticated monitoring and control mechanisms. Battery Management Systems (BMS) are critical in mitigating risks tied to degradation, thermal runaway, and suboptimal energy utilization by accurately tracking SoC—the available charge quantification—and SoH, which indicates cumulative battery aging and capacity fade. Traditional BMS approaches employing static rule-based algorithms and equivalent circuit modeling lack the flexibility to adapt dynamically to real-world, nonlinear battery responses, motivating the adoption of data-driven AI techniques. Recent advances in ML models including Random Forests, Support Vector Regression, and deep learning architectures such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) have demonstrated superior predictive capabilities for both charge state estimation and degradation forecasting. Additionally, integrating IoT sensors enables continuous, cloud-enabled monitoring and facilitates automated safety interventions. Furthermore, reinforcement learning frameworks are being investigated to optimize operational strategies for second-life energy storage batteries. This paper critically reviews these developments, focusing on their theoretical frameworks, practical implementations, and the resulting improvements in BMS intelligence and robustness.

Role of Battery Management Systems (BMS)

Lithium-ion batteries' widespread application across electric vehicles, renewable energy storage, and portable electronics underscores the necessity for comprehensive BMS to maintain performance integrity, operational safety, and lifecycle extension. Central to the BMS functionality is the precise quantification of State of Charge (SoC), which dictates the residual usable capacity and prevents detrimental conditions such as overcharging or deep discharge. Parallelly, real-time evaluation of State of Health (SoH) offers prognostic insights into capacity degradation and internal resistance increments, informing maintenance schedules and end-of-life estimations. Thermal regulation forms another integral function; by continuously monitoring temperature gradients and utilizing active (e.g., liquid coolants) or passive (e.g., phase change materials) dissipation mechanisms, the BMS mitigates thermal runaway risks, a critical safety concern. Fault detection modules employ sensor fusion to identify abnormal parameters indicative of cell imbalance, gas emissions, or electrical faults and subsequently initiate protective actions including circuit isolation, power cutoffs, or alarms. Additionally, cell balancing algorithms—either active or passive—equalize charge distribution across battery cells to minimize performance degradation due to cell mismatches. Collectively, these functionalities necessitate advanced control architectures capable of real-time decision-making, fault tolerance, and communication with external monitoring systems, which are increasingly realized through AI and IoT integrations.

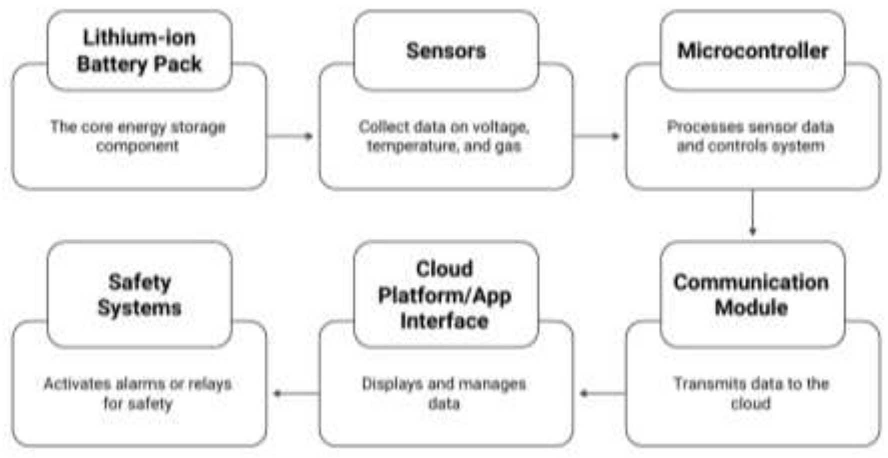

Figure 1: Functional Architecture of Battery Management System

AI Techniques for SOC and SOH Estimation

Accurate estimation of SoC and SoH is paramount for optimizing battery utilization and safety. Traditional electrochemical and Coulomb counting methods are prone to cumulative errors and are limited by fixed initial conditions, which hampers their accuracy in practical deployments. AI and ML approaches, particularly deep learning models like LSTM and GRU, excel at capturing temporally correlated data patterns from multivariate sensor inputs including voltage, current, and thermal metrics. These recurrent neural networks effectively model the battery's sequential dynamics and facilitate long-term degradation trend analysis, often outperforming classical methods in dynamic scenarios. Feedforward Neural Networks (FNNs) configured with multiple input parameters also provide a balance between model complexity and estimation accuracy when resource constraints are a consideration. For SoH prediction, ensemble methods such as Random Forest regressors have demonstrated robustness by leveraging large, labelled datasets (e.g., NASA's Prognostics Center benchmarks), achieving high coefficient-of-determination (R^2) and low error margins (RMSE). Hybrid models combining neural networks with fuzzy inference systems (ANFIS) further enhance resilience against noisy data and environmental uncertainties. The growing availability of high-fidelity sensor data and advances in AI model architectures are expected to continually improve estimation reliability and computational efficiency.

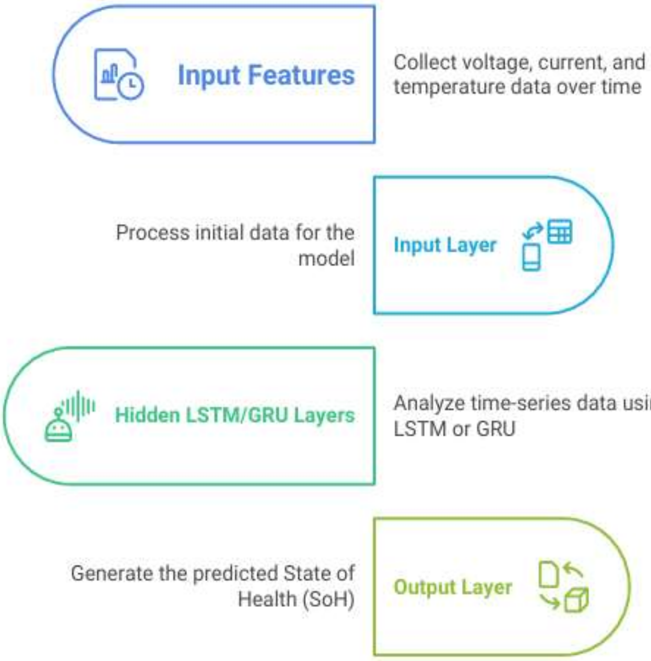

Figure 2. Deep learning framework using LSTM/GRU networks for long-term SoH forecasting based on time-series battery data.

Fault Detection and Thermal Management

Ensuring battery safety requires not only effective charge state estimation but also proactive fault identification and thermal control to prevent catastrophic failures. Conventional threshold-based fault detection often fails to cope with sensor inaccuracies and environmental variability. AI-driven classifiers, including convolutional neural networks (CNNs) and deep residual learning models such as Improved Binary Deep Residual Networks (IB-DRN), have been employed for high-accuracy anomaly detection at near 98%, identifying faults like overvoltage, short circuits, gas leaks, and thermal runaway precursors. These models process multi-sensor datasets and provide real-time diagnostic outputs driving relay actuation, alarms, and shutdown protocols. Regarding thermal management, AI optimizes hybrid cooling solutions integrating active liquid cooling with phase change materials and thermoelectric components by modeling real-time heat dissipation across multi-cell arrays. Advanced thermal simulations coupled with AI-based control enable dynamic modulation of cooling intensity aligned with battery load and environmental conditions, thereby extending battery lifespan while ensuring operational stability.

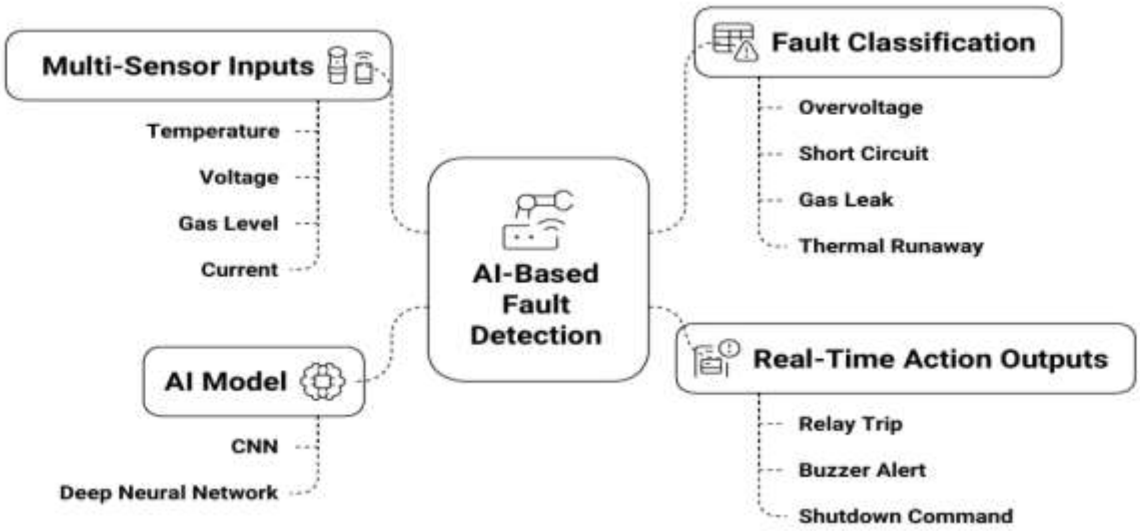

Figure 3. Fault classification architecture using multi-sensor input and CNN-based AI detection modules.

IoT-Integrated Smart BMS

The fusion of IoT with AI introduces a paradigm shift in BMS capabilities, transforming isolated battery cells into networked, intelligent systems. IoT-enabled BMS architectures consist of distributed sensors capturing voltage, current, temperature, and gas concentrations, interfacing with microcontrollers for edge processing and communicating via wireless protocols such as Wi-Fi, GSM, or Bluetooth to cloud-based platforms. This connectivity supports continuous data streaming, cloud analytics, predictive maintenance, and remote diagnostics. Platforms like ThingSpeak facilitate scalable data visualization and control, enabling fleet-level management of energy storage systems. IoT integration allows near-real-time responses to abnormal battery conditions through automated control commands or alerts, supporting preventive interventions that reduce downtime and maintenance costs. This interconnected infrastructure supports large-scale deployment scenarios, enhancing adaptability and operational efficiency in dynamic environments.

Table 1. Common IoT components and their roles in real-time monitoring, control, and fault protection in smart Battery Management Systems.[2] Roy et al., 2023; [5] Jaiswal et al., 2023

IoT Component	*Measured/ Controlled Parameter*	*Technology Used*	*Function in BMS*
Voltage Sensor	Voltage	Voltage divider, INA219	Detect over/ undervoltage in cells
Temperature Sensor	Temperature	LM35, DS18B20	Trigger thermal control (fan, shutdown)
Current Sensor	Charge/ Discharge current	ACS712, Hall Sensor	Monitor load & estimate SoC
Microcontroller	Data Acquisition & Processing	ESP32, STM32	Control, processing, and decision-making
Communication Module	Wireless Data Transmission	Wi-Fi, GSM, Bluetooth	Send data to cloud or mobile app
Cloud Platform	Data Storage & Visualization	ThingSpeak, Firebase	Perform analytics and remote monitoring
Relay/Buzzer System	Fault Triggering	Controlled by MCU	Cutoff or alert system in case of anomalies

Predictive Modeling and Second-Life Applications

AI-enabled predictive modeling offers foresight into battery performance trajectories, facilitating optimized maintenance and replacement strategies. A growing research emphasis lies in repurposing second-life lithium-ion batteries—previously used in electric vehicles but still viable for stationary energy storage applications. Deep Reinforcement Learning (DRL) algorithms have been deployed to learn adaptive charge-discharge policies based on real-time state information and external variables such as energy market dynamics and grid demand fluctuations. Architectures combining Long Short-Term Memory (LSTM) networks with Proximal Policy Optimization (PPO) provide robust policy learning for economic dispatch in renewable energy systems, balancing battery degradation costs against revenue optimization. These approaches enhance second-life battery utilization efficiency, delay recycling needs, and contribute to circular economy goals by extending battery service life in less demanding roles.

Conclusion

Artificial Intelligence is fundamentally reshaping Battery Management Systems by introducing unprecedented levels of precision, adaptability, and integration. AI-powered SoC and SoH estimations, coupled with intelligent fault detection and dynamic thermal management, significantly improve battery safety and operational efficiency. The incorporation of IoT further empowers BMS with real-time monitoring, remote control, and scalable analytics, while predictive modeling techniques advance second-life battery applications toward sustainable energy storage solutions. Despite challenges such as data privacy, standardization, and model generalizability, the trajectory firmly points toward AI-augmented BMS becoming an indispensable component in the evolving energy landscape, underpinning innovations in electric vehicles, smart grids, and renewable integration.

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