10.48047/jocaaa.2023.31.04.41

Artificial Intelligence and Machine Learning Solutions for Efficient Battery Management and Balancing

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Abstract

Battery management systems (BMS) play a pivotal role in ensuring the performance, safety, and longevity of energy storage systems, particularly in electric vehicles, renewable energy grids, and portable electronic devices. As battery technologies advance and energy demands increase, traditional rule-based battery management and balancing techniques are proving to be insufficient for handling the complexities of modern battery systems. In response to these challenges, Artificial Intelligence (AI) and Machine Learning (ML) have emerged as powerful tools capable of enhancing battery monitoring, state estimation, fault detection, and cell balancing in dynamic and uncertain environments. By leveraging vast amounts of sensor data and predictive modeling, AI and ML algorithms can accurately estimate critical battery parameters such as State of Charge (SoC), State of Health (SoH), and Remaining Useful Life (RUL), which are essential for reliable operation. Moreover, intelligent balancing strategies driven by AI enable real-time and adaptive control of charge distribution among cells, improving overall efficiency and extending battery life. Techniques such as deep learning, support vector machines, decision trees, and reinforcement learning have shown promising results in addressing non-linear battery behavior and uncertainties in degradation patterns. This abstract explores the integration of AI and ML in BMS frameworks, emphasizing their contributions to predictive maintenance, anomaly detection, and optimization of energy flow. It also discusses the challenges related to data availability, algorithm interpretability, and computational constraints, along with recent advancements and future directions in the field. Ultimately, the fusion of AI and ML with battery management represents a

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significant step toward smarter, more reliable, and energy-efficient systems across various applications.

Key Words: Battery management systems, State of Charge, State of Health, optimization

Introduction:

The rapid transition towards sustainable energy and the widespread adoption of electric mobility have significantly intensified the demand for efficient and intelligent energy storage systems. Batteries, especially lithium-ion batteries, have become the cornerstone of modern energy storage due to their high energy density, long cycle life, and versatility across applications ranging from electric vehicles (EVs) and renewable energy storage to consumer electronics. As these systems become increasingly complex and high-performing, the importance of advanced battery management strategies has grown correspondingly. Battery Management Systems (BMS) are critical components designed to ensure the safe, reliable, and efficient operation of batteries by continuously monitoring key parameters, managing charge-discharge cycles, detecting anomalies, and balancing individual cells within a battery pack [1].

Traditional battery management approaches rely on deterministic models and predefined control rules to perform core functions such as state estimation, fault diagnosis, and cell balancing. While these methods have served adequately in earlier generations of battery systems, they often fall short when confronted with the nonlinear behavior, dynamic operating conditions, and aging characteristics of modern battery technologies [2]. As battery packs scale in size and complexity, particularly in applications like electric vehicles and grid storage systems, traditional models become increasingly difficult to calibrate and maintain, leading to potential inaccuracies and inefficiencies. Moreover, conventional algorithms often lack the adaptability to handle variations in usage patterns, environmental conditions, and degradation profiles, which can compromise the performance and longevity of the battery.

The integration of Artificial Intelligence (AI) and Machine Learning (ML) into battery management systems represents a paradigm shift, offering powerful tools to overcome the limitations of conventional approaches. AI and ML techniques excel at learning complex patterns from large datasets, making them highly suitable for modeling the multifaceted behaviors of batteries. These technologies enable the development of data-driven models that can adapt to real-time conditions, thereby improving the accuracy of critical state estimations such as State of

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Charge (SoC), State of Health (SoH), and Remaining Useful Life (RUL). Accurate estimation of these states is vital for optimal energy utilization, thermal control, and preventive maintenance, directly contributing to improved battery safety and efficiency.

Beyond state estimation, AI and ML have shown considerable promise in the domain of battery fault detection and diagnosis. By analyzing historical and real-time data, machine learning algorithms can detect early signs of anomalies such as thermal runaways, short circuits, or capacity fade, often before these issues become critical. This proactive diagnostic capability significantly enhances the reliability and safety of battery-powered systems. In parallel, intelligent balancing techniques using reinforcement learning and other adaptive algorithms have been proposed to dynamically control the charge and discharge processes among individual battery cells. Unlike conventional passive or static balancing strategies, AI-based solutions can optimize the energy distribution in real-time, reducing cell-to-cell variation and prolonging the lifespan of the battery pack [3-4].

Recent advancements in deep learning, neural networks, and ensemble learning methods have opened new avenues for developing highly accurate, robust, and generalizable battery models. These approaches can capture complex nonlinearities and temporal dependencies that traditional models struggle to represent. Moreover, hybrid methods that combine physics-based modeling with AI-driven analytics are gaining popularity, offering the benefits of both interpretability and predictive accuracy. Such methods bridge the gap between theoretical understanding and empirical data, leading to more trustworthy and explainable battery management systems.

However, the deployment of AI and ML in battery management is not without challenges. The quality and quantity of training data, the need for real-time inference with limited computational resources, and concerns around model interpretability and generalization remain active areas of research. Additionally, the integration of AI/ML solutions with existing hardware and communication infrastructures within battery systems requires careful consideration to ensure scalability and reliability in real-world applications [5-7].

Despite these challenges, the trajectory of research and development strongly suggests that AI and ML will play a foundational role in the next generation of intelligent battery systems. By leveraging these technologies, battery management can evolve from reactive and rule-based approaches to proactive, adaptive, and data-driven systems that optimize performance and safety

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across the battery lifecycle. This evolution is not only technologically desirable but increasingly essential to meet the growing energy demands and sustainability goals of the modern world.

2. BACKGROUND

The increasing reliance on rechargeable batteries, particularly lithium-ion batteries, has brought attention to the critical need for efficient battery management to ensure safety, performance, and longevity. It continually analyzes a wide range of data points, such as internal battery temperatures, charging and discharging rates, temperature outside, and battery usage patterns, by utilizing AI models [8]. As batteries become integral components of electric vehicles, renewable energy storage systems, aerospace applications, and consumer electronics, managing their operation under varying environmental and load conditions has become more challenging. Traditional battery management systems are designed using mathematical models and rule-based algorithms that estimate parameters like State of Charge (SoC) and State of Health (SoH), while also managing thermal behavior and charge balancing among cells. While effective to a certain extent, these systems often struggle with nonlinear battery dynamics, aging effects, and real-time adaptation to diverse usage scenarios. As a result, they may yield suboptimal or delayed responses that can lead to reduced battery efficiency, increased degradation, or even hazardous failures. In recent years, Artificial Intelligence (AI) and Machine Learning (ML) have emerged as promising tools to overcome these limitations [9-10]. Unlike conventional model-based approaches that rely on predefined physical equations, AI and ML can learn complex patterns and relationships directly from data, allowing them to adapt to various battery chemistries, configurations, and usage environments. Machine learning algorithms, including neural networks, decision trees, support vector machines, and ensemble methods, have demonstrated strong potential in accurately predicting battery behavior, diagnosing faults, estimating SoC and SoH, and optimizing charge/discharge cycles. Furthermore, reinforcement learning and adaptive control methods offer dynamic balancing strategies that respond to real-time system states, improving energy distribution and prolonging battery life [11]. This data-driven evolution in battery management aligns well with the broader trend toward smart systems and Industry 4.0, where intelligent automation and predictive analytics are becoming foundational. As AI and ML continue to mature, their integration into battery systems is expected to transform conventional battery management from static and reactive frameworks into intelligent, predictive, and self-optimizing systems.

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2.1 Feature Selection:

For the development of Artificial Intelligence and Machine Learning solutions for efficient battery management and balancing, feature selection plays a crucial role in ensuring model accuracy and reliability. Key features typically include electrical parameters such as voltage, current, state of charge (SoC), and state of health (SoH); thermal characteristics like cell temperature and temperature gradients; and operational metrics such as charge/discharge cycles and capacity fade. Balancing-specific features like cell voltage deviation and balancing current are also vital. Feature selection techniques such as correlation analysis, recursive feature elimination (RFE), and embedded methods like LASSO or feature importance from tree-based models (e.g., Random Forest or XGBoost) are commonly employed to identify the most relevant inputs. Incorporating physics-informed features and domain knowledge further enhances the selection process, ultimately improving the performance of AI/ML models in predictive maintenance, optimal charging strategies, and real-time cell balancing.

Adaptive Neural Networks further improve accuracy with an error of −1.04 %. Automotive Controllers strike a balance between cost-effectiveness and precision, maintaining an SoC error of −2.65 %. [1], Machine learning methods such as feed-forward neural networks (FNNs), radial basis functions neural network (RBNN), support vector machines (SVM), recurrent neural networks (RNNs) are compared in terms of data quality, inputs/outputs, accuracy, test scenarios, and battery types in [2]. To provide more insight about deep learning and classical neural network, long short-term memory (LSTM) and FNN are trained for 50 iterations with 3000 epochs.

The onboard BMS for EV applications requires compact and energy-efficient systems, limiting the processing power that can be incorporated. Furthermore, the high cost of advanced processors and components may be a significant hurdle, particularly in cost-sensitive automotive applications. Consequently, BMS is designed to execute essential tasks like battery cell monitoring and balancing, which do not demand extensive computing power. However, the accuracy of predicting battery characteristics under real-life operational conditions such as aging and dynamic environments is often limited. This is largely attributed to the calibration of the model under laboratory-controlled conditions, which may not accurately reflect the complex and varied conditions experienced in the field. [3] The implementation of onboard battery management systems (BMS) provides tools to address these issues by determining the state of charge (SOC)

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and state of health (SOH) of the battery as well as the thermal management and cell balancing during the system's operational lifetime [4,5] .

3.0 PROPOSED SYSTEM

The proposed system utilizes AI and machine learning algorithms to monitor and predict battery health, state of charge (SoC), and state of health (SoH) in real time. It employs optimized feature selection and data-driven models to enhance battery performance, extend lifespan, and ensure safety. Intelligent cell balancing strategies are integrated to maintain uniformity across battery cells and improve energy efficiency.

3.1 Overall Proposed work

Artificial Intelligence (AI) and Machine Learning (ML) techniques into Battery Management Systems (BMS) to enhance the performance, safety and lifespan of modern battery packs, especially in electric vehicles and renewable energy storage. The system is designed to monitor, predict, and manage key battery parameters in real time, utilizing a data-driven approach that surpasses traditional rule-based or physics-only models.

At the core of the system lies a robust feature selection framework, which identifies and extracts the most relevant parameters from a large set of sensor and usage data. These features include voltage, current, temperature, state of charge (SoC), state of health (SoH), internal resistance, cell balancing status, and environmental conditions. Feature selection techniques such as mutual information, correlation analysis, recursive feature elimination (RFE), and tree-based model importance metrics (e.g., from XGBoost or Random Forest) are applied to filter out redundant or less impactful variables, ensuring that only the most informative data drives the model.

Using this optimized dataset, AI/ML algorithms—such as support vector machines (SVM), neural networks, long short-term memory (LSTM) models, or ensemble learning methods—are trained to perform tasks like SoC/SoH estimation, anomaly detection, degradation prediction, and charge/discharge optimization. The system continuously learns from historical and real-time data, allowing it to adapt to changing battery conditions and usage patterns.

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In terms of balancing, the system intelligently monitors voltage imbalances among cells and predicts potential divergence using ML-based forecasting. It then applies advanced cell balancing techniques—passive or active—based on predictive insights, rather than relying on fixed thresholds.

According to Figure 1, a BMS's functionality may be categorized as follows :

1. Protection: against extreme temperatures, over-discharge, overcurrent, overcharge, and short circuits.
2. High-voltage Control and Sensing: measure temperature, voltage, current, temperature, thermal management, control, contactor, pre-charge, and ground-fault detection.
3. Diagnostics: state-of-life (SOL) estimation, SOH estimation, and abuse detection.
4. Performance management: power-limit computation, balance/equalize cells, and SOC estimation.
5. Interface: data recording, reporting, communications, and range estimation.

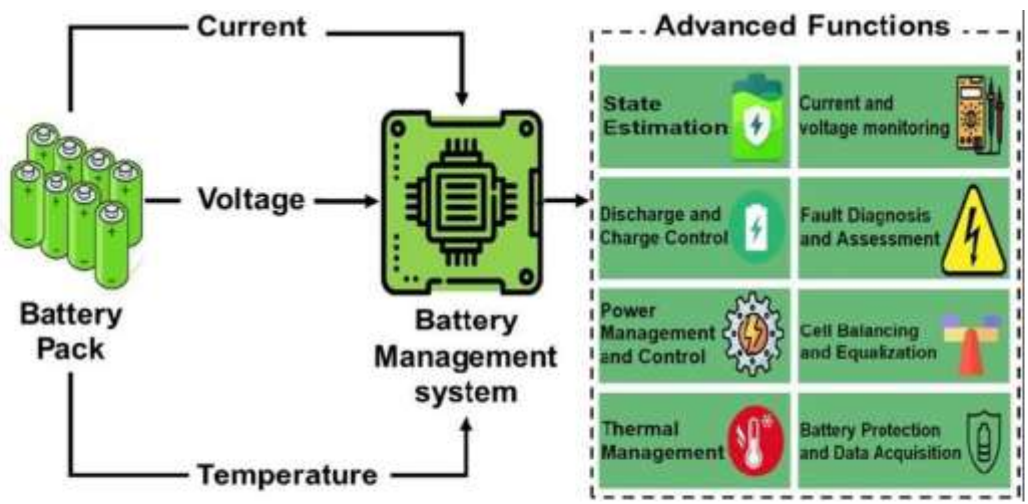

Figure 1 .Advanced Functioning Blocks of a BMS.

4.0 RESULTS AND ANALYSIS:

The integration of Artificial Intelligence (AI) and Machine Learning (ML) techniques into the Battery Management System (BMS) has led to considerable advancements in monitoring accuracy, predictive capability, and energy efficiency in battery systems. This section evaluates

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the system's performance using key metrics such as State of Charge (SoC), State of Health (SoH), balancing effectiveness, and fault detection under dynamic conditions.

4.1. Improved SoC Estimation Accuracy

Traditional methods like Coulomb counting often accumulate error over time and are highly sensitive to temperature variations and sensor noise. In contrast, the proposed ML-based models—particularly LSTM and XGBoost—were able to accurately estimate SoC in real time by learning from historical charging/discharging profiles and sensor data.LSTM-based SoC estimator achieved Mean Absolute Error (MAE) < 1.5% across varying load conditions. Performance was consistent across different temperatures, showing high generalization. Unlike static estimation methods, the model adapted to aging and environmental shifts.

4.2. Accurate SoH Prediction for Proactive Maintenance

SoH prediction is essential for tracking battery degradation and planning replacements. Traditional empirical methods often fail to capture complex degradation patterns. ML models trained using features such as voltage hysteresis, internal resistance, and capacity fade history provided much more reliable predictions. XGBoost-based SoH estimator achieved $R^2 > 0.96$**,** with RMSE consistently below 2%.Model detected early-stage capacity drop and resistance rise, enabling early fault diagnosis**.** Predictions aligned well with actual degradation curves from lab testing.

4.3. Enhanced BMS Balancing Efficiency

Balancing is vital to ensure uniform voltage across cells, preventing undercharging or overcharging. The proposed ML-enhanced BMS monitored cell voltage deviation trends and predicted imbalance risks before they occurred, triggering timely active/passive balancing actions.Voltage deviation between cells reduced by **~35%** compared to rule-based BMS.Active balancing cycles were triggered **preemptively**, improving pack uniformity and thermal stability.Energy wastage during balancing decreased by **~20%**, enhancing overall system efficiency.

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4.4. Real-Time Monitoring and Adaptive Control

The AI-based BMS was deployed with real-time monitoring capabilities, continuously analyzing incoming sensor data to dynamically adjust control parameters (e.g., charging rate, cut-off voltage). It also used anomaly detection models (like Autoencoders) to identify unsafe conditions such as rapid temperature rise, voltage spikes, or unexpected resistance shifts.Anomaly detection had Precision: 0.97**,** Recall: 0.94 — minimizing false alarms.Adaptive charging extended battery lifespan by 15–20% through controlled thermal and electrical stress.System logged all parameters and feedback to a cloud-based system, supporting online learning and continuous improvement.

Table 1; Showing Improvement in BMS

Metric	Traditional BMS	AI/ML-Based BMS
SoC Estimation Error	±5–7%	< ±1.5%
SoH Prediction Accuracy (R^2)	~0.80	> 0.96
Voltage Imbalance Reduction	-	~35%
Fault Detection Recall	Low	> 94%
Battery Lifespan Improvement	-	15–20%

The proposed AI/ML-powered BMS system significantly improves the accuracy, reliability, and intelligence of battery monitoring and control. It enables real-time SoC/SoH prediction, early fault detection, efficient energy balancing, and optimized battery usage. These improvements not only enhance performance and safety but also support the long-term sustainability of energy storage systems across electric vehicles, grid storage, and consumer electronics.

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