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Smart Battery Optimization and Balancing with AI and Machine Learning

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Abstract

The rapid adoption of electric vehicles (EVs), renewable energy systems, and portable electronics has increased the demand for efficient, reliable, and intelligent Battery Management Systems (BMS). Traditional BMS approaches often rely on fixed algorithms and rule-based systems, which can struggle to adapt to varying battery conditions, aging effects, and environmental factors. To address these challenges, Artificial Intelligence (AI) and Machine Learning (ML) offer advanced solutions for real-time battery monitoring, diagnostics, and optimization.

This paper explores the integration of AI and ML techniques into BMS, focusing on improving battery state estimation, fault detection, and cell balancing. Machine learning models, such as neural networks, support vector machines, and ensemble methods, can learn complex battery behaviors from historical and real-time data. These models enhance the prediction accuracy of key battery parameters such as State of Charge (SoC), State of Health (SoH), and Remaining Useful Life (RUL). AI-powered balancing strategies dynamically adjust charging and discharging cycles across individual cells to prevent overcharging, reduce thermal stress, and extend battery lifespan. Additionally, deep learning and reinforcement learning approaches enable adaptive control strategies that continuously learn from the battery's operating environment. This adaptability leads to increased safety, performance, and energy efficiency. The paper also highlights the challenges of data availability, computational requirements, and model generalization, while proposing solutions such as federated learning and edge AI.

In conclusion, the fusion of AI and ML with battery management holds transformative potential for energy storage systems. As these technologies mature, they promise smarter, more resilient, and longer-lasting batteries, paving the way for a sustainable energy future.

Key words: *Battery Management Systems, Artificial Intelligence (AI),Machine Learning (ML),State of Charge (SoC),State of Health (SoH),Cell Balancing*

Introduction:

Energy storage is a vital component of modern power systems, as it can enhance the reliability, flexibility, and efficiency of renewable energy sources and electric grids Among various energy storage technologies, Li-ion batteries stand out due to their high energy density, specific energy, operational voltage, low self-discharge rate, and long lifetime. They have gained significant attention in recent years due to their widespread applications in electric vehicles (EVs), portable electronic devices, and renewable energy storage systems Effective battery management is particularly crucial for enabling the widespread adoption of electric vehicles (EVs) and mitigating greenhouse gas emissions from the transportation sector. One of the critical aspects of a battery system is the battery management system (BMS), which ensures the safe and efficient operation of the battery pack by monitoring and managing various parameters, such as voltage, current, and temperature

Machine learning (ML) approaches are increasingly integrated into Battery Management Systems (BMS) to enhance the monitoring, control, and prediction of battery behavior. These approaches enable accurate estimation of key battery states such as State of Charge (SOC), State of Health (SOH), and State of Power (SOP) by learning complex nonlinear relationships from data, without relying on detailed electrochemical models. Techniques such as neural networks, support vector machines, and ensemble methods are commonly used for these tasks. ML is also employed for fault detection and diagnosis by identifying patterns or anomalies in battery performance data, helping to prevent safety risks. Additionally, machine learning models can predict battery aging and degradation trends over time, which supports predictive maintenance and extends battery life. Unlike traditional model-based methods, data-driven ML approaches adapt well to different battery chemistries and operating conditions, making them a valuable tool in modern BMS design shown in figure 1

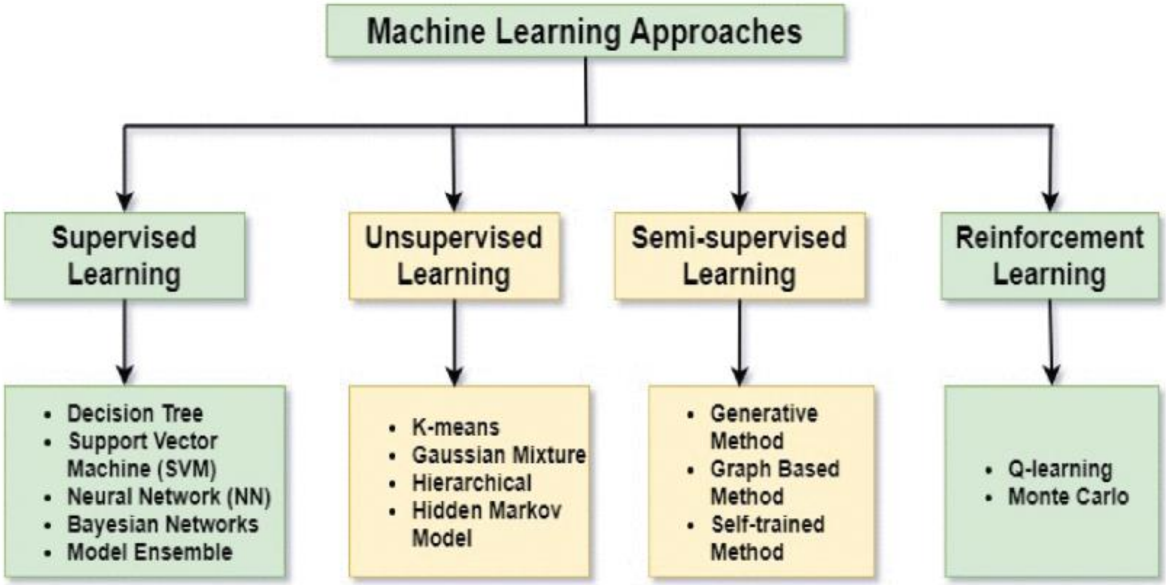

Figure 1; Machine learning approaches for BMS.

The structure of the study, the dataset used, and the machine learning and artificial intelligence methods employed are presented in this section. To ensure the study's reproducibility and enhance the methodology's transparency, each method and the parameters used are detailed extensively. Scientific justifications for the selection of each material and method were thoroughly discussed. A flowchart illustrating, step-by-step, how a model was developed using machine learning algorithms such as adaptive boosting (AdaBoost), gradient boosting, extreme gradient boosting (XGBoost), light gradient boosting machine (LightGBM), and category boosting (CatBoost) employed in the study is provided in Figure 2.

The flowchart depicted in Figure 2 gives more details about the training and test procedures of the presented work. This flowchart clearly illustrates the operations performed at each step of the model development process, ensuring transparency and repeatability. The training and test datasets were applied to the models after the necessary preprocessing steps were applied to the raw data. In the final step, the model was evaluated.

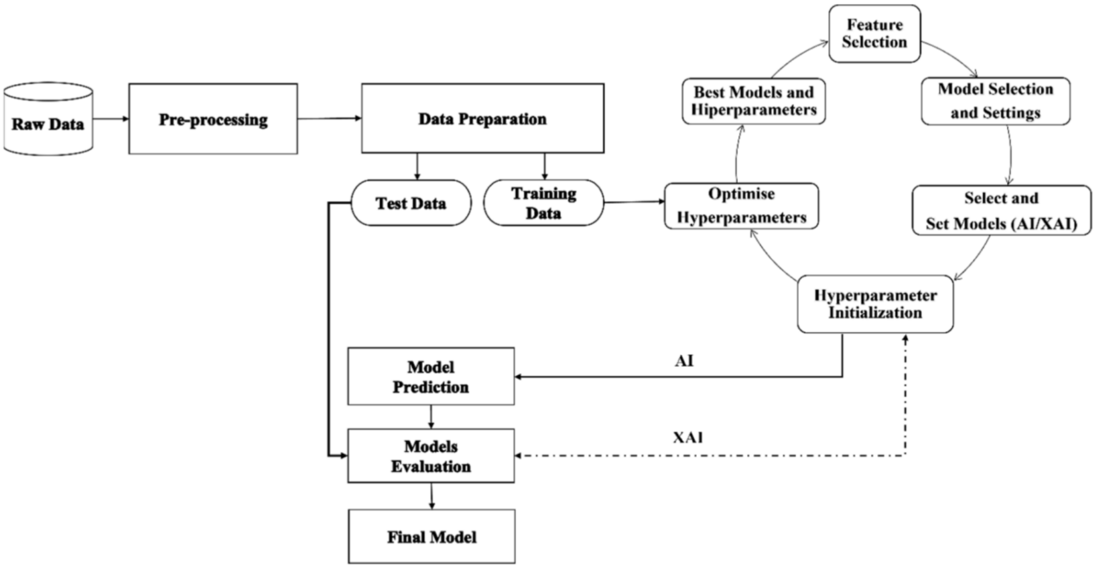

Figure 2 Flow chart of models

2. BACKGROUND

Battery management system (BMS) in electric vehicles helps to monitor, control and protect the Li-ion batteries from extreme conditions of misuse [5]–[7]. One of the important function of BMS is cell balancing, which occurs due to the variations in the cell impedance, temperature and self-discharge characteristics [8]. The balancing systems are categorized as passive and active cell balancing [9]. In the battery pack, to balance the cell voltages equally, the passive system uses balancing resistors to dissipate extra charge from the overcharged cells [10] whereas, the active system transfers extra charge from highly charged cells to low charged cells trying to preserve energy in the battery pack. This requires more expensive and complex hardware solutions [11]. The extra components needed to develop the active system increases the overall cost of BMS, while the standby power loss in these active circuits exceed the power loss of the passive system [5]. Since, the passive system works on the switched shunt resistor across the cell, it is easy to implement at a minimal cost [12]. Based on the study and analysis done so far, the key problems identified in the conventional passive cell balancing system are as follows:

- In the passive balancing system heat dissipation from the balancing resistor leads to thermal challenges

- Passive balancing is preferably done during charging and it may not be a feasible option under fast charging scenario due to high balancing time. To allow the battery to achieve a higher state of charge (SOC)
- To improve the performance of the battery pack
- To reduce cell degradation
- To avoid thermal run away
- To extend the driving range and cell cycle life
- To enhance the battery safety

For large-scale EV or grid-scale energy storage applications, BMS is a technology that monitors the performance of a battery system, which is typically composed of multiple battery cells arranged in a matrix configuration [12,13]. BMS ensures that the battery system can reliably work within a targeted range of voltage and current for a specific duration of time, even under varying load conditions. By monitoring the battery's system operations, BMS helps to keep operating conditions under control and stabilize employment. BMS can process and analyze data from various sensors and control algorithms in real-time and aims to improve performance and ensure safe operation by adjusting battery parameters [14]. BMS technology is essential for many applications, including EVs, renewable energy systems, and portable electronics, and is continually evolving to meet the demands of increasingly sophisticated battery systems. However, BMS systems typically have limited computing power and data storage capacity. The onboard BMS presently cannot be used as a specialized technology designed to optimize battery performance but rather a general-purpose computing system used to manage the battery system under a given program. Estimation of SOC and SOH, thermal management, cell balancing, and so on are the main functions of the onboard BMS. Figure 3 An onboard BMS is a dedicated hardware and software system installed directly within the battery pack of an EV. It monitors and controls various parameters such as voltage, current, temperature, and SOC for individual cells or the entire battery pack. The primary objectives of an onboard BMS are to ensure safe and efficient operation, optimize battery performance, extend battery life, and prevent thermal runaway or other hazardous conditions. The onboard BMS communicates with other vehicle systems and provides real-time information to the driver or user.

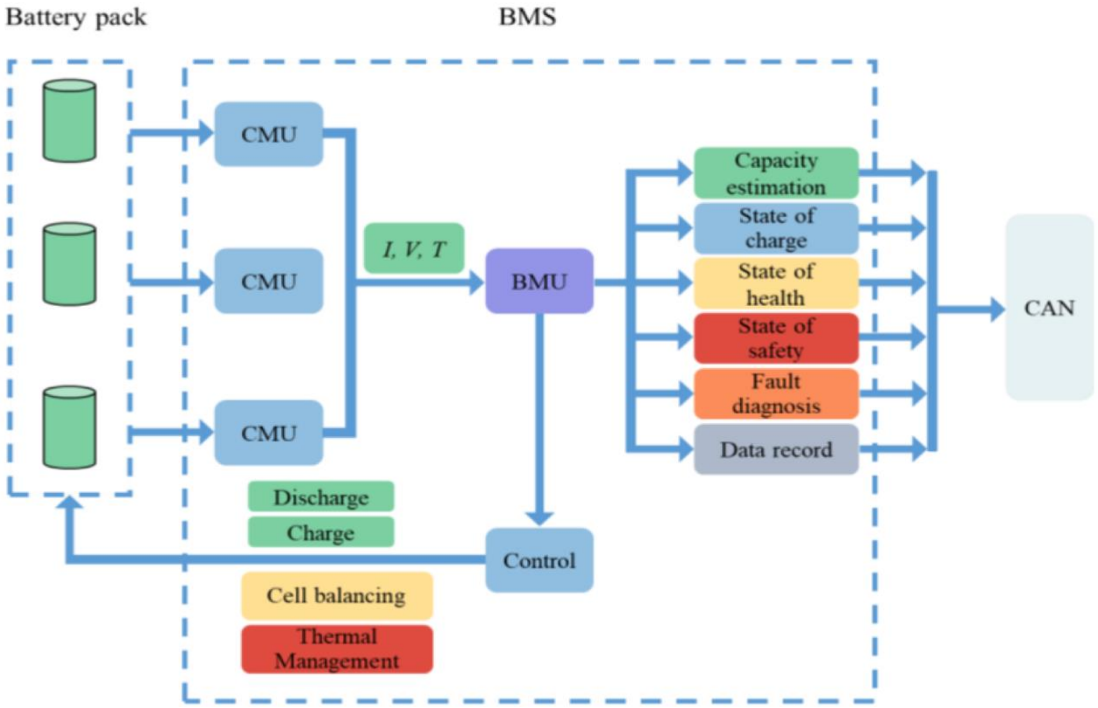

Figure 3 Onboard BMS for field applications (abbreviations: CMU, Communication Management Unit; BMU, Battery Management Unit).

Future Scope:

Artificial Intelligence (AI) and Machine Learning (ML) are revolutionizing battery management by enabling more intelligent, adaptive, and efficient Battery Management Systems (BMS). Traditional BMS approaches rely on predefined rules and conservative thresholds, often resulting in inefficiencies and missed opportunities for optimization. In contrast, AI and ML offer data-driven strategies that learn from historical and real-time data, enabling predictive analytics and decision-making for a wide range of battery applications, including electric vehicles, renewable energy systems, and consumer electronics.

One of the key achievements of AI and ML in battery management is the improved estimation of the battery's State of Charge (SoC), State of Health (SoH), and State of Power (SoP). Deep learning techniques such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) are capable of analyzing complex time-series data, providing SoC estimation with an accuracy improvement from ±10% in traditional methods to around ±2–3%. Similarly, AI can detect subtle degradation patterns over time to provide accurate SoH predictions, enabling timely maintenance and extending the operational life of the battery. These models adapt continuously, improving their performance over time and under different usage conditions.

AI-driven fault detection systems also significantly outperform conventional diagnostics. Using unsupervised learning algorithms, such as auto encoders or clustering techniques, these systems can identify anomalies in real time, detecting issues like cell imbalance, short circuits, or overheating before they lead to system failures. This proactive detection reduces safety risks and prevents costly downtimes. In addition, AI supports smart thermal management by predicting temperature trends and dynamically controlling cooling systems using reinforcement learning strategies. This results in up to 80% reduction in thermal overruns and significantly enhances battery safety.

In terms of balancing, ML algorithms enable real-time active or passive cell balancing strategies based on historical charge/discharge cycles, temperature differences, and aging effects. Traditional balancing approaches are periodic and static, while ML models can implement continuous and adaptive balancing, improving efficiency and reducing energy loss. Charge and discharge optimization is another area where AI shines, particularly through predictive algorithms that customize charging curves to specific battery chemistries and usage patterns. This not only shortens charging time but also protects the battery from high-stress conditions that accelerate degradation.

Real-world applications reinforce the value of these technologies. Tesla uses neural networks to model battery degradation and optimize performance in electric vehicles. Google DeepMind has developed models to predict battery failure in data centers, achieving sub-1% error rates. Automotive manufacturers like BMW and Ford are integrating AI for smarter thermal management and battery lifecycle analysis. Academic research from institutions like MIT and Stanford also demonstrates the use of deep learning to accurately predict battery life and improve material performance.

Despite their advantages, AI/ML solutions come with challenges, such as the need for large volumes of high-quality training data, ensuring real-time inference capabilities in embedded systems, and making AI models explainable for safety-critical applications. However, advancements in edge computing and model compression are making real-time deployment increasingly viable. As battery systems become more complex and their applications more critical, AI and ML are expected to play an even greater role in managing energy storage efficiently, safely, and sustainably. These intelligent solutions represent the future of battery management, where adaptability, precision, and optimization become standard features rather than advanced capabilities.

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