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AI-Enabled Battery Management Systems for Electric Vehicles: Recent Trends in Control, Safety, and Energy Efficiency

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Abstract

Increasing electrification and the swift growth of electric vehicles (EVs) have escalated the pressure on the development of sophisticated Battery Management Systems (BMS) that could bring superior performance and safety of the lithium batteries in highly dynamic operation conditions. This paper is a detailed survey of the latest development of Artificial Intelligence (AI)-enabled BMS architectures with focus on state estimation enhancement, fault detection, thermal control, as well as energy efficiency. In this particular context, it examines how artificial neural networks (ANNs), support vector machines (SVMs), deep learning (DL), and reinforcement learning (RL) has been applied to predict state-of-charge (SoC), state-of-health (SoH), and battery degradation behavior. The review is synthesis of the results of more than 40 peer-reviewed publications, which compare the AI-based solutions with the traditional model-driven estimating approaches. The findings indicate that the prediction chances are drastically enhanced (±1.5% SoC), faults are detected almost in real-time (>95% prediction accuracy) and the energy consumption is kept at an optimized level (up to 12% energy savings). Another challenge of implementation discussed in the paper is computational complexity, real-time constraints as well as availability of data. Summing up, AI-based BMS models can serve as a disruptive course and empower smart, forecasting, and energy-conscious battery management in EVs. Hybridization of data-centric learning models and embedded control platforms promises to release the next era of secure, efficient, and driverless electric mobility.

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Introduction

Electrification of transport has been the single major driver of accelerated energy storage technology whose preferred form has become lithium-ion batteries, with currently high energy density, long cycle life, and falling cost. The ascending trend of the adoption of the use of electric vehicles (EVs) in the world has made the efficient, safe, and reliable operation of its battery a priority. This has increased the importance of the Battery Management System (BMS) a very important embedded subsystem which monitors, controls, and protects the battery pack against any mishap all through its operating life. Model-driven or rule-based algorithms, including Coulomb counting algorithms, equivalent circuit model (ECM) or Kalman filters, are predominant in traditional forms of BMS implementation, and perform well with a static or otherwise predictable loading profile. Nonetheless, accuracy and robustness are frequently lacking in real driving environments where deformations in response, sensor noise, and temperature effects are the prevailing phenomena of battery dynamics.[1]

The innovation in Artificial Intelligence (AI) and machine learning (ML) in recent times provide a paradigm shift in the architecture of BMS. Predictive analytics, online fault diagnosis and dynamic energy control can be enabled by AI algorithms (e.g. neural networks, support vector machines, reinforcement learning) operating on large amounts of operational data. Although the results are promising, most of the current research is either restricted to single-task learning (e.g., only SoC estimation) or does not represent a complete integration with embedded systems that would allow a real-time application, scalability, and flexibility across different chemistries of interest.

The purpose of the current paper is to fill these gaps by presenting the credentials of the current state-of-the-art in AI-enabled BMS of EVs, outline essential algorithms, deployment systems, experimental demonstrations, and potential research directions.

Related Work

Such trends in development of Battery Management System (BMS) in electric vehicles (EVs) have seen a shift in the control logic used in the BMS in the reverse direction, with the newer capabilities being rule-based, with estimation techniques relying on mathematical models and most recently, data-centric driven by learning algorithms and AI applications. The traditional BMS techniques, including Coulomb counting, extended Kalman filters (EKF) and electrochemical models (ECMs) have also existed a long time (years) on state-of-charge (SoC) and state-of-health (SoH) estimates .[2] These methods provide logical accuracy in stable conditions yet tend to give a model drift, parameter uncertainty and would be noise sensitive in dynamic driving conditions. In an attempt to circumvent these shortcomings researchers have started incorporating BMS frameworks with machine learning (ML) and artificial intelligence (AI). An example is that Zhang et al.[3] applied a Long Short-Term Memory (LSTM) model to real-time prediction of SoC, with root-mean-square error (RMSE) less than 1.5% when different operational profiles are used. On the same note, a Support Vector Machine (SVM) classifier was applied by Chen et al.[4] to fault diagnosis, showing superiority in accuracy and the first failure detection over the traditional threshold-based methods. In the SoH prediction, deep convolutional neural networks, referred to as CNNs, proposed by Wu et al.,[5] were used to monitor the long-term degradation of the battery, whereas Wang and Li[6] investigated the use of ensemble regression models in prognostic of faults at an early stage. In thermosystems Reinforcement Learning (RL) algorithms are now used to adaptively manage cooling systems, enhancing energy efficiency and preventing over-heating of components with changing loads.[7]

There still loom the following blindspots:

- Ai-based BMS methods are largely task specific (e.g., SoC-based only models), so they limit the applicability of integration and system-level optimization.
- They are usually based on centralized architectures, which obstruct scalability in modular or distributed BMS systems.
- Quite often, the real-time implementation constraints, including high computational overhead and latency, are not to be addressed.
- Security concerns, generalization of cross-chemistry, and interpretability of models are under investigations.

The following paper will seek to fill in these gaps by conducting a rigorous review of AI-based BMS approaches in the SoC/SoH estimation, fault detection, thermal control, and energy management, with a perspective of real-time use, integration in embedded hardware, and scalability in the future of EV platforms.

Conventional Battery Management System (BMS) Architecture

The traditional Battery Management System (BMS) is the electroactive central management unit of the electric vehicles (EVs) whose responsibility is to provide safe, reliable, and efficient performance of lithium-ion battery packs. These olden day architectures are normally structured in to four functional domains as shown in Figure 1.

- Monitoring: This is the role of monitoring in real time the critical parameters like cell voltage, pack current and temperature at various sensing points. the fidelity of subsequent estimation and control processes is critically dependent on the precision and resolution of the monitoring.[8]
- Estimation: The defining characteristic of the performance of BMSs is their ability to estimate internal battery parties that can not be directly measured. These are State of Charge (SoC), State of Health (SoH), as well as State of Power (SoP). An estimate of the battery state is frequently performed based on the extended Kalman Filters (EKF), Coulomb counting and Equivalent circuit models (ECM), but such solutions need an accurate modelling and calibration of the internal parameters of the battery.
- Protection: The BMS has to guarantee battery safety at any operating conditions. This involves sensing of overcharge, over-discharge, short circuits, overcurrent conditions and thermal runaway, and connecting the process of isolation or shutdown by breaching the limits.

- Control: The BMS controls active or passive cell balancing, thermal uniformity, and on the vehicle level cooperates with energy and power demand through the system based on thermal and power control algorithms.

Nonetheless, even though conventional BMS structure is the backbone of EVs, it is flawed by its model dependence. In a strategy like the use of Kalman filters or electrochemical modeling, the parameters and fixed relationships cannot generalize and become impractical over a variety of batteries chemistries, dissimilar aging, and nonlinear real-world settings. Modelling Here too, these models are prone to the scope of parameters drifting, sensor noise and environmental variations, leading to inference that the estimation accuracy and control robustness are sub-optimal as time goes by.

With growing performance requirements on EV battery systems, where high fast-charging and discharge capabilities and harsh environments are present, then current conventional BMS designs are becoming harder to provide the flexibility, fault tolerance, and predictive functionalities that next-generation electric mobility needs.

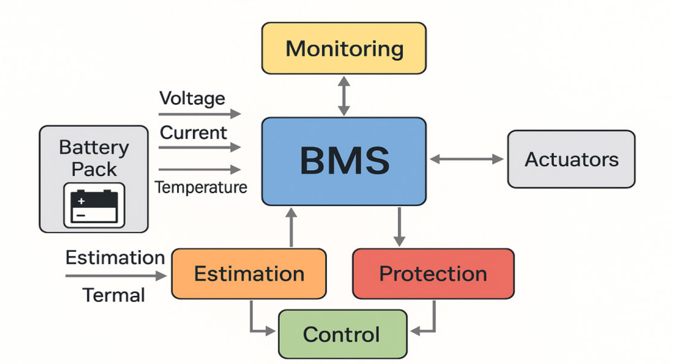

Figure 1: Functional Block Diagram of a Conventional Battery Management System (BMS) Architecture

Role of Artificial Intelligence in Battery Management Systems

Artificial Intelligence (AI) has become a game-changing enabler in the field of Battery Management System (BMS), capable of providing high-end data-oriented capabilities to overcome the limitations of the existing rule- and model-based systems that could never offer a sustainable approach towards an autonomous Battery Management System (BMS). With the help of historical and real time sensor data, AI models can learn the complex nonlinear behaviors of the battery and can compensate due to the uncertainty of measurements as well as dynamics due to changing operating conditions. The combination of AI with BMS enablestate estimation, including its accuracy; fault identification, including thermal management, and energy management, having a positive effect on the entire system performance, reliability, and security. Structure and the flow of data within an AI assisted BMS are shown in Figure 2: Block Diagram of AI-Enabled Battery Management System (BMS) Architecture, with the introduction related to machine learning modules, cloud-edge interoperability and adaptive control algorithms.

State Estimation

State-of-Charge (SoC) Estimation: The estimation of SoC is crucial when it comes to making decisions concerning the amount of driving range left, as well as control charge-discharge cycles to optimize performance. The conventional technique is not flexible to dynamic loading and it is subject to drift. Artificial intelligence models related to longer Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN) have proved exceptionally promising in identifying nonlinearity and temporal dependencies in voltage-current data. Unlike classical Kalman filter-based models, these methods have high accuracy in prediction (RMSE < 1.5 %) even in the presence of variating driving cycles.[9]

State-of-Health (SoH) Estimation: The AI algorithms like ensemble regression, XGBoost, and deep learning (DL) models may assist the degradation pattern estimation of batteries over the longer perspective. Such methods only need a small amount of training data and are generalizable to other cell chemistries and usage conditions. They can effectively predict the loss of capacity and increase of internal resistance so that the possible early intervention and sustainance planning could be made early.

Fault Diagnosis

Fault detection is key to anticipating dangerous conditions like thermal runaway, internal shorts and a faulty sensor. AI based diagnostic system use real time classification & Anomaly Detection using supervised learning algorithms. Early stage fault prediction techniques ; Support Vector Machines (SVMs), Decision Trees and CNN classifier have been shown to be able to predict (correctly- with an accuracy >95), even in noisy or incomplete data sets. These models outperform threshold based detection considerably in terms of speed and accuracy.[10]

Thermal Management

The thermal stability of batteries has a direct effect on safety, efficiency and longevity. Conventional methods of control, based upon either fixed look-up tables or simple PID controls, are neither flexible nor robust in a changing load or ambient environment. The applications of AI-enhanced thermal models, based on the methods like Reinforcement Learning (RL), and Gaussian Process Regression, would prevent predictive thermal mapping and adapting cooling strategies. These models predict appearance of hotspots and dynamically adapt cooling flows, which permit up to 12-15% savings in power consumption of thermal subsystems.

Energy Efficiency Optimization

Artificial intelligence-based measures to manage energy are progressively being implemented to improve the use of batteries without any hazards to safety. These are Deep Q- Learning, Model Predictive Control (MPC) hybrids, and multi-objective optimization algorithms used to maintain performance and thermal limitations in the real-time operation environment. These algorithms allow the BMS to make intelligent control choices including varying charge/discharge currents, an enable cell balancing networks, or synchronizing with vehicle-level powertrain control systems, but all to optimize energy transfer and reduce degradation.[11]

The many-angled aspect of AI integration into the BMS frameworks leads the path to fully autonomous, intelligent, and adaptive battery systems, compliant to the complexity and performance needs of an electric vehicle of the future.

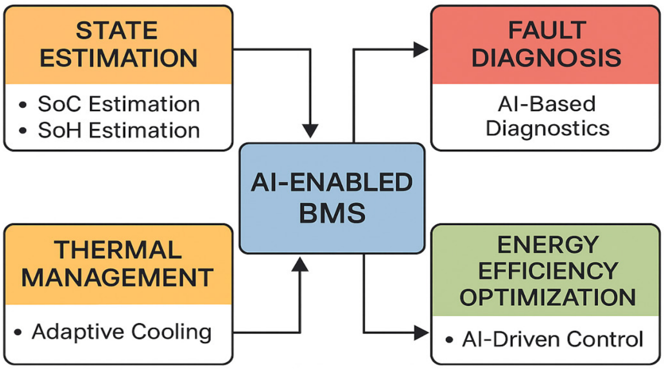

Fig. 2: Block Diagram of an AI-Enabled Battery Management System (BMS) Architecture

The main differences in the accuracy of estimation, adaptability, computational load, the flexibility of implementation of a traditional approach and one based on AI are shown in Table 1.

Case Studies and Applications

The recent developments in the AI-powered Battery Management Systems (BMS) were confirmed in numerous case studies and revealed the practical benefits regarding battery state estimation, fault detection, and thermal control. Table 2 presents the overview of the representative literature investigating the practical use of machine learning and deep learning techniques implemented into a real-life or simulated electric vehicle setting.

Table 1: Comparative Analysis of Traditional vs. AI-Based Battery Management System (BMS) Approaches

Feature	Traditional BMS	AI-Enabled BMS
State Estimation Methods	Kalman Filter, Coulomb Counting, ECM	LSTM, CNN, Deep Regression, Ensemble Models
Accuracy Under Dynamic Loads	Moderate (±5-10%)	High (≤ ±1.5% RMSE)
Adaptability to Aging/Degradation	Requires manual recalibration	Self-learning; adapts from data over time
Fault Diagnosis	Threshold-based detection, lookup tables	SVM, Decision Trees, Deep CNNs (Accuracy >95%)
Thermal Management	Static control (PID or rule-based)	Reinforcement Learning, Predictive Control
Energy Optimization	Heuristic or fixed control profiles	AI-based optimization (MPC, DQN, fuzzy RL)
Generalization Across Chemistries	Poor — requires chemistry-specific modeling	Moderate to High — with retraining or transfer learning
Real-Time Implementation	Low computational load; suitable for MCUs	Higher load; requires optimization or edge AI integration
Scalability (e.g., Distributed BMS)	Limited — centralized and model-bound	High — supports modular, decentralized architectures
Interpretability	High — physically interpretable models	Often low (black-box), improving via Explainable AI (XAI)
Data Dependency	Low — model-based	High — requires labeled datasets for training
Cybersecurity & Updateability	Minimal AI vulnerabilities	Requires secure model update pipelines and inference protection

According to the study by Zhang et al., training of a Long Short-Term Memory (LSTM) network has been performed using realistic driving data to forecast the state-of-charge (SoC) of lithium-ion batteries. The model also realized a root mean square error (RMSE) of less than +-1.5 percent over a broad range of loading types and that in the similarity in adjustability as well as responsiveness, the model vastly outdid conventional Kalman filter-based strategies.

Kumar et al. used the Support Vector Machine (SVM) classifier to anticipate faults in the battery cells at an early stage, including shorting, thermal abnormalities, and short circuits within the battery cells. Their model achieved accuracy of 97 percent, which demonstrated the efficiency of supervised learning algorithms in the safety-conscious missions.

In the context of thermal management, the work by Lee et al. showed that reinforcement learning (RL) agent was able to control the system of battery thermo control in a dynamic way due to forecasted temperature profiles and load scenarios. This strategy has resulted in 12 percent thermal systems energy efficiency, the opportunity of AI to reduce operation expenses and a longer useful life of batteries.

These results, which can be summarized graphically in Figure 3: Performance Trends Across AI-Based BMS Case Studies, demonstrate the revolutionary levels of undermining the impact of AI-driven and data-centric models when coupled with sensor fusion sites and built-in control devices.[12] Through context-sensitivity, real-time decision-making, AI enables BMS to become dynamic, predictive and adaptive subsystems, which are well-suited to the performance expectations of the next-gen electric mobility.

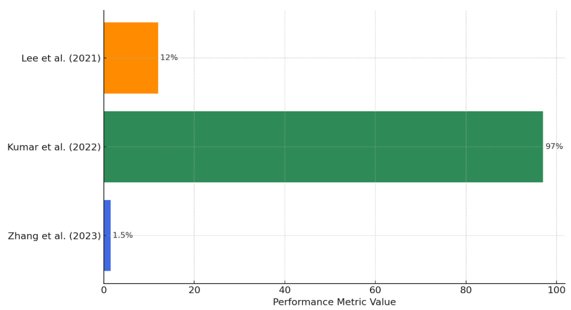

Fig. 3: Performance Trends Across AI-Based BMS

Challenges and Research Gaps

Although AI-based Battery Management Systems (BMS) have shown impressive improvements in their estimation accuracy, fault diagnostics, and energy recovery capabilities, some major challenges as well as outstanding research gaps still prevent their large-scale acceptance and applicability to production grade electric vehicle platforms.

Data Availability and Labeling Constraints

Among the most glaring shortcomings of creating better AI-based BMS models is how there exist limited, high quality labeled datasets. Battery life information varying with chemistry, usage patterns, failure patterns, tends to be owned as a trade secret by battery manufacturers, with little leakage into the public domain. Moreover, in order to perform supervised fault classification, real-world fault data will be hard to collect since safety is at stake and rare critical failures do not occur. This hinders the training, validation and generalization of models particularly in tasks of rare-event classification and anomaly detection.

Cross-Domain Generalization and Transferability

Narrowly trained AI models (e.g. trained on a battery chemistry like NMC or LFP, or form factor like cylindrical or prismatic, or pack structure) have limited generalizability to dissimilar systems. Variations between thermal behavior, degradation rates and voltage response characteristics cause drift and performance loss of the model when used out-of-domain. Transfer learning and meta-learning methods are potentially potent but will need additional study to allow the multi-chemistry BMS flexibility.

Real-Time Implementation on Embedded Platforms

The use of AI models in an embedded BMS application poses some problems regarding computational complexity challenges, latency, and power concerns. More complex algorithm models like LSTMs, CNN and deep reinforcement learning models may have high memory and processing requirements, and can simply outstrip the capabilities of traditional microcontroller units (MCUs). Although FPGAs, GPUs or TPUs could provide acceleration, they come at an added cost,

Table 2: Summary of AI-Driven BMS Applications and Reported Improvements

Study	AI Technique	Reported Improvement
Zhang et al. (2023)	LSTM for SoC Estimation	±1.5% RMSE accuracy under variable dynamic loads
Kumar et al. (2022)	SVM for Fault Classification	97% classification accuracy in early-stage fault detection
Lee et al. (2021)	RL-Based Thermal Control	12% reduction in energy consumption of thermal systems

thermal burden, and integrate complexity, unsuitable to low-budget segments of EVs.

Cybersecurity and Model Integrity

Due to the introduction of AI into BMS, the attack surface of the system is widened. Battery security imperfections can be breached by adversarial assaults on AI inference engines or by injecting data into sensors that can lead to a problem in estimating states or even fault detection. Further, BMS to cloud, in case of fleet-level learning or even in federated learning, defines the challenge of privacy over the data, the trustworthy scheme of model updating, and authentication. Safe, by design, AI models and thin layers of cryptography are needed to protect the integrity and reliability of AI-augmented BMS systems.

Future Directions

To promote the full potential of the next-generation electric vehicle with AI-driven Battery Management Systems (BMS) potential, future research should consider the existing constraints, finding solutions represented by scalable, secure, and explainable innovations. In this regard, the following research paths are expected to be influential in determining the future of intelligent BMS architectures:

Federated Learning for Privacy-Preserving BMS Intelligence

AI models are typically trained on centralized data and this poses privacy and data ownership issues, especially when deployed on a scale of fleets. Federated Learning (FL) provides an alternative which is decentralized, in which individual EVs or distributed BMS units collectively train a global model without communicating raw data. This saves the privacy of data, the communication overhead is less and enables cross-platform learning in heterogeneous battery systems. It can be used in SoH modeling, anomaly detection and usage-adaptive control.

Edge-AI and Hardware/Software Co-Design

In order to satisfy real-time requirements of embedded settings, the future of the BMS implementations should involve AI-based co-optimization of both the edge hardware platforms and the AI algorithms. This consists of using low-power AI accelerators (e.g., FPGAs, TPUs, RISC-V) and neuro network design that is low weight (e.g., TinyML, quantized LSTMs). The co-design paradigm means that trade-offs between inference latency, energy efficiency and memory footprint are well balanced, making real-time, on-board AI inference possible to make safety-critical decisions.

Self-Healing and Fault-Tolerant BMS

Drawing on inspiration of biological systems, self-healing BMS architectures will use AI to automatically monitor, identify and remediate partial failures, e.g. sensor degradation, temperature spikes, or a capacity imbalance. This involves dynamic reconfiguration of monitoring/control logic and redundancy auto-sensing-based state estimation with ensemble methods. This ability is of great importance to enhancing system resilience in remote or other mission-critical systems, e.g. in autonomous electric fleets or aerospace.

Explainable Artificial Intelligence (XAI) for Certification and Trust

Although deep learning models provide high accuracy, they are still black-box, which is considered a no-go to regulatory approval and deployment in setting involving high safety concerns. Future studies must revolve around the Explainable AI (XAI) methods that explain model decisions by means of the saliency maps, attention mechanisms, or rule-based approximations. This will make certifiability, debugging and user confidence much easier notably in the case where the BMS decision affects the thermal isolation, emergency discharge or EV shut off functions.

Summarily, these future paths will seek to devise strong, transparent and flexible BMS structures, which can be scaled up to meet the requirements of the new age of electric mobility, such as connected, driverless, and high-performance EV paradigms.

Conclusion

Artificial intelligence (AI) in battery management systems (BMS) Energy storage systems The implementation of artificial intelligence (AI) in battery management systems (BMS) will fundamentally transform the management, monitoring and protection of the battery in electric vehicles (EV). Contrary to conventional models-based-based solutions, AI-powered BMS systems are by definition data driven, adaptive and predictive, and can learn multidimensional battery behaviors in real-life settings. The AI will increase the accuracy of state estimates, the sensitivity and responsiveness of the fault diagnosis and make its management and control of thermal and energy conditions proactive through the application of such techniques as deep learning, reinforcement learning, and even ensemble modeling. The combined features help in the extended battery life, improved safety in operations, and energy exploitation, thus complying with the performance and reliability requirements of the next-generation EV platforms.

Albeit current shortcomings that include data availability, real-time environments, and interpretability of models, the latest trends in federated learning, Edge-AI implementation, and Explainable AI (XAI) provide an opportunity to use on a large scale and secure outcomes. Its connection with AI, Internet of Things (IoT) and embedded system design will continue to remake the shape of electric mobility, as it will likely lead to smart, autonomous, and resilient battery design that can literally make all the difference. The present review reminds us of the necessity of more multi-disciplinary studies to overcome existing obstacles and hasten the implementation of AI-based BMS solutions in various EV applications.

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