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Principles and Research Progress of Lithium Battery Management Systems for New Energy Vehicles

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Abstract

Lithium-ion batteries have become the cornerstone of New Energy Vehicles (NEVs) owing to their high energy density, long cycle life, and high energy efficiency. Nevertheless, there is an increasing need for the integration of a complex battery functionality, safety and longevity. This article critically evaluates recent advances in the principles, developmental trends, and research progress of lithium battery management systems developed for NEV applications. The paper examines the basics of battery types, BMS architecture, state estimation methods, safety features, thermal control, and the next generation technology, including AI-based diagnostics and wireless technology. Also, the second-life applications, circular economy strategies and policy standardization are given special attention. The review highlights several important challenges and opportunities, including real time state estimation, small-scale hardware integration, and constraints in high-speed charging, as well as opportunities in solid-state BMS, federated learning, and cyber-physical simulation platforms. Overall, the article offers a perspective on the future of intelligent, safe and sustainable battery systems in academia and industry.

Keywords

Lithium-Ion Battery, Battery Management System, New Energy Vehicles

1. Introduction

1.1. Background on Lithium Batteries and New Energy Vehicles

The adoption of the electric propulsion of vehicles after internal combustion engines (ICE) is a significant milestone towards the decarbonization of the transportation industry. New energy vehicles (NEVs) such as battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) primarily rely on lithium-ion batteries as their principal electrochemical energy-storage systems owing to their high energy density, cycle characteristics, and safety properties [1]-[3]. Fuel Cell Electric Vehicles (FCEVs), on the other hand, rely on hydrogen fuel-cell stacks for their propulsion energy, and lithium-ion batteries are generally used as auxiliary energy-storage devices for peak-power assistance, regenerative braking energy recovery, and transient load balancing [4]. These have been further spurred by the issue of greenhouse gas emission of internal combustion engine vehicles around the world and the simultaneous advancement of cleaner energy storage technologies [5] [6]. The battery is the most crucial component of EVs. Lithium-ion batteries offer distinct advantages, including high energy and power densities, environmental friendliness, and long-term durability [7]. However, its performance, life, and safety are quite sensitive to temperature [8]. The battery can ensure high efficiency and an appropriate working state at 15˚C - 40˚C [9].

1.2. Significance of Battery Management Systems

Although battery chemistry is under continuous development, the success of any battery system is also reliant on its management. Since the battery serves as the primary energy source of an electric vehicle, improper management can significantly accelerate degradation, reduce performance, and compromise operational safety. Hence there is the need to be cautious when utilizing the battery to ensure a reliable and continuous performance and extended lifespan [10]. Currently, the predominant focus of TMS research lies in the temperature control of the battery and cabin [11] [12]. The battery management system (BMS) is relevant in maintaining maximum usage of energy, safety and durability of battery packs. These parameters are state of charge (SOC), state of health (SOH), state of power (SOP), state of temperature (SOT), thermal parameters, and fault diagnosis which it monitors and regulates [13] [14]. BMS aims at extending the life of Lithium-Ion cells and consequently the battery system through the control of the temperature level and distribution [15]. The BMS (Particularly in high-performance NEVs) enables safe operation via prevention of overcharge, overheating, and cell imbalance to ensure that users are not threatened, and lifecycle cost-efficiency is enhanced.

Common cooling approaches that have been developed to battery thermal management systems (BTMS) are air cooling [16], liquid cooling [17], phase change materials (PCM) [17], heat pipe [18] [19], and thermoelectric cooling [20]. Fewer researches have been conducted on thermoelectric cooling [21]. The BTMS based on air cooling is no longer applicable to EVs with high safety consideration and endurance because of low heat conductivity rate [22]. Although PCM cooling system is a proprietor of an excellent cooling performance, cost and mass of the system are not negligible [23]. The application of heat pipe cooling requires additional cooling mechanisms to fulfill the condensation part, and this increases the cost [24].

1.3. Motivation, Structure of the Review, and Research Gaps

Though the lithium battery and the BMS technologies have achieved commendable initiatives, many challenges remain. These include robust modeling in a dynamical system, real-time approximation of the multi-state (SOC, SOH, SOP) and cell balancing between age-related differences, and seamless interaction with AI, cloud computing and vehicular internet technologies [25]. This review fills this deficiency as it describes recent advances in battery types and board architecture and identification of emerging issues in post-lithium chemistries and intelligent diagnostics and sustainable end-of-life management.

1.4. Review Methodology

This review was carried out by a systematic search on literature on lithium-ion battery management systems for new energy vehicles. Main databases searched were Web of Science, Scopus, IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar. Literature search was conducted by using the combinations of keywords such as "Battery Management System", "Lithium-ion Battery", "Electric Vehicle", "State of Charge", "State of Health", "Battery Thermal Management System", "Cell Balancing", "Fault Diagnosis", "Wireless BMS", and "Artificial Intelligence Battery Management". The publications were chosen mainly in the time range from 2017-2025, to cover the latest developments, and some earlier key publications that provided the foundations for the BMS concepts. Only peer-reviewed journal articles, conference papers of significant technical relevance, international standards and authoritative review papers were included. Publications that did not have enough technical information or unrelated to automotive battery management were not included. The selected literature was divided into battery technologies, battery modeling, state estimation, safety management, thermal management, intelligent BMS technologies, and end-of-life management, and then synthesized by using thematic analysis. Comparative analysis was done to find out the current research trends, technological limitations and future research opportunities.

2. Electrochemical Energy Storage and Battery Management System Fundamentals

2.1. Overview of Battery Types: Pre-Lithium, Lithium-Ion, and Post-Lithium

Battery development has shifted to high-performance lithium-ion chemistries replacing lead-acid and Nickel-based batteries. Early hybrids utilized pre-lithium, Ni-MH and Ni-Zn batteries, which had moderate energy densities. Their use was limited, however, by the care life and energy density limitation.

Lithium-ion batteries of high energy (260 Wh/kg), large cycle life and moderate cost are the leading technology. They include LFP ($LiFePO_4$), NCM (nickel-cobalt-manganese), and NCA (nickel-cobalt-aluminum) chemistries, each of which is designed to be either safe, energy-saving, and/or cost-effective [26]. Post-lithium systems such as solid-state batteries (SSBs), lithium-sulfur (Li-S), lithium-air

($Li-O_2$), and sodium-ion batteries are all potential breakthroughs in battery safety and energy density. However, they have restrictions of price, bad conductivity, and cycle life [27]. The evolution of battery technologies from conventional chemistries to next-generation systems is depicted in Figure 1.

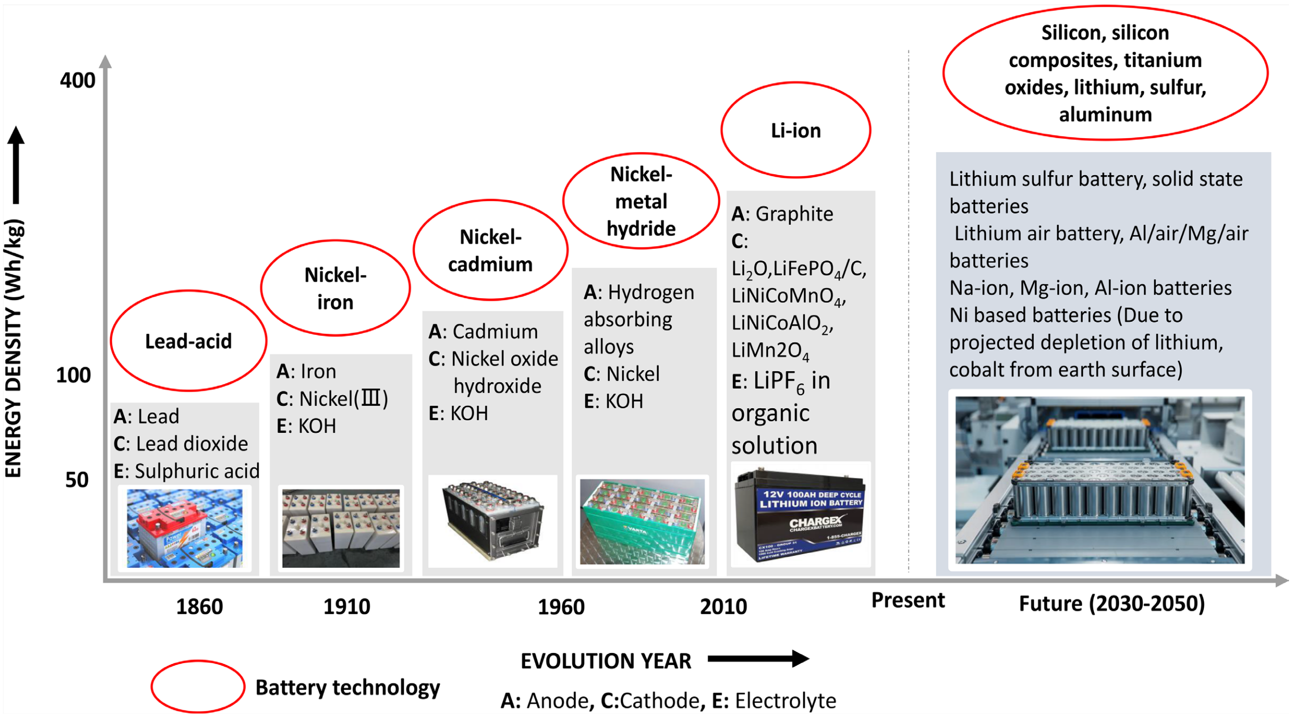

Figure 1. Evolution of battery technologies from conventional chemistries to next-generation solid state and sodium-ion systems.

Although lithium-ion batteries remain the dominant battery type for NEV, LFP batteries have excellent thermal stability, long cycle life, and have lower cost, which makes them attractive for entry level passenger EVs and commercial vehicles. On the other hand, NCM and NCA batteries have much higher energy density but are more energy sensitive to thermal runaway and therefore need more sophisticated thermal management and safety control. While promising to deliver better safety and energy density, emerging post-lithium chemistries face significant challenges such as high interfacial resistance, limited cycle stability, and manufacturing scalability, and thus cannot meet future NEV requirements without corresponding improvements in BMS intelligence and control algorithms.

2.2. Basic Functions and Definitions of Battery Management Systems

A BMS is a set of hardware and software that is implemented to monitor, control and optimize battery consumption. Core functions include:

- State estimation (SOC, SOH, SOP, SOT): This refers to using models and sensor data to infer internal battery states. State of Charge (SOC) is the amount of charge stored in the battery expressed as a percentage and is used to schedule charging and discharging, and to estimate driving range. The State of Health

(SOH) is an indicator of battery degradation and remaining useful life (RUL) and is crucial for maintenance planning and end-of-life assessment. State of Power (SOP) is defined as the maximum charging or discharging power that can be safely supplied at any given time, allowing for power limiting and fast-charging control. State of Temperature (SOT) is a thermal state of the battery used for thermal protection, activation of battery cooling and heating, and thermal derating to ensure safe and efficient battery operation. SOC serves as an input for several computations performed by the BMS, including SOH, power calculations, and cell balancing [28]. Conventionally SOC attains 100% when the battery is fully charged and descends to 0% upon depletion. Conversely, SOH initiates at 100% when the battery is manufactured, gradually reducing to 80% at the termination of its operational life, described as end of life (EoL) [29]-[31].

- Thermal management: Maintaining optimal operating temperature to ensure degradation or thermal runaway is prevented.
- Fault diagnosis: Early detection of short circuits, sensor failures, or thermal anomalies.
- Charge/discharge control and balancing: Maintaining a consistent operation of the cells, and extracting as much energy as possible [13] [32].

BMS also interacts with vehicle control and charging infrastructure and makes more and more use of AI and IoT capabilities, which are also becoming more and more used.

As illustrated in **Figure 2**, the BMS integrates sensing, estimation, protection, and communication modules to ensure safe and efficient battery operation.

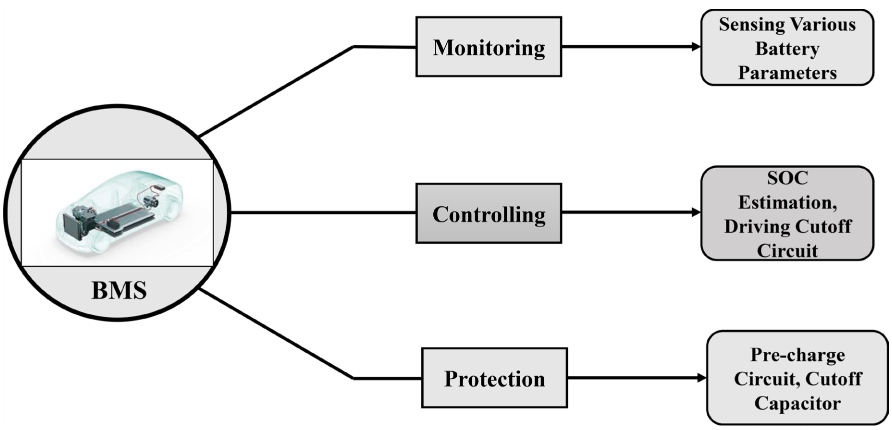

Figure 2. Basic schematic of battery management system.

2.3. Battery Management and Thermal Management Coordination

Battery Management Systems (BMS) and Battery Thermal Management Systems (BTMS) are closely related, but they have different responsibilities. The BMS is mainly responsible for battery monitoring, state estimation, protection, fault diagnosis, communication and supervisory control. The BTMS, however, controls the battery temperature to keep it within the desired operating range using cooling, heating, airflow management and coolant circulation. The BMS usually gathers the thermal sensing information and transmits it to the BTMS controller, and the BTMS performs cooling or heating actions using actuators such as pumps, valves, fans, compressors, or heaters. Therefore, modern electric vehicles are increasingly moving towards the coordinated BMS-BTMS architectures where thermal decisions are jointly optimized with the battery state estimation and thermal feedback.

2.4. BMS Topologies: Centralized, Modular, Distributed

- Centralized BMS: All battery cells are monitored and controlled from a single controller. This approach is cost-effective but limited in scalability and fault tolerance [5].
- Modular BMS: The battery modules have BMS units that have their own master controller. The topology provides a balance between flexibility and control [2].
- Distributed BMS: Each cell or a small group of cells has a dedicated microcontroller, enabling high granularity, better fault isolation, and redundancy. However, it comes with increased complexity and cost [1] [13].
- Wireless BMS (wBMS): It involves the wireless connection between cell monitors and the main controller without physical communication wires.
- Cloud-Connected or IoT-Enabled BMS: BMS is connected to a cloud server on which the data are uploaded to assist with cloud-based analytics, diagnostics, or second-life insights.

Figure 3 summarizes the principal BMS topologies adopted in modern electric vehicles.

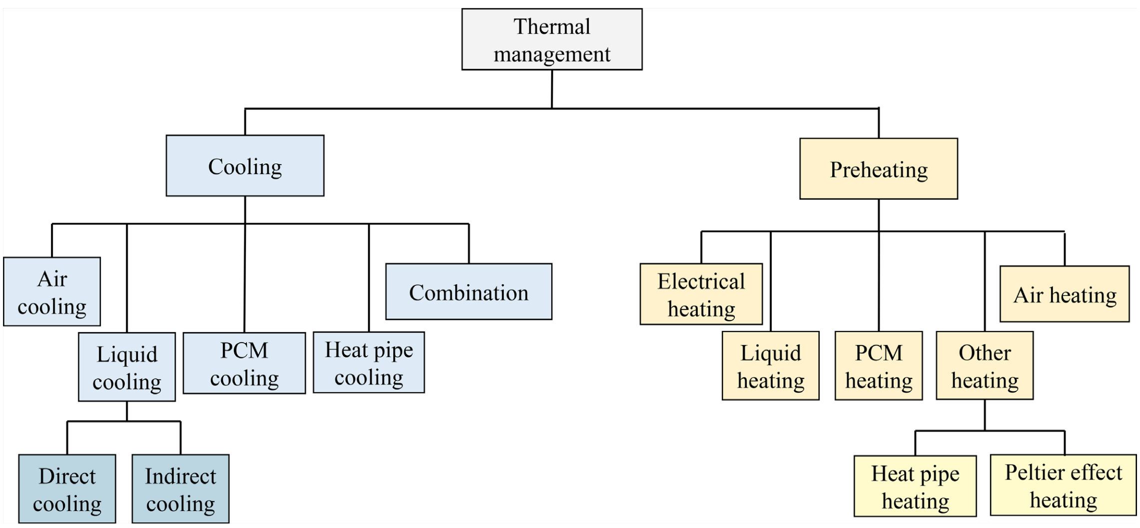

Figure 3. Comparison of centralized, modular, and distributed BMS architectures.

3. Battery Modeling and State Estimation in Battery Management Systems

Battery modeling and state estimation are the computational components of Battery Management Systems (BMS), which allow the accurate and real-time management of the state of charge (SOC), state of health (SOH) and remaining useful life (RUL) of lithium-ion batteries used in electric vehicles (EVs). With the maturation in electric vehicle technology, these estimation tasks are no longer the subject of simple linear approximations, but instead there is hybridization between physics-based and artificial intelligence (AI) methods [5]. **Figure 4** presents the different methods of SOC estimation classified into four main categories.

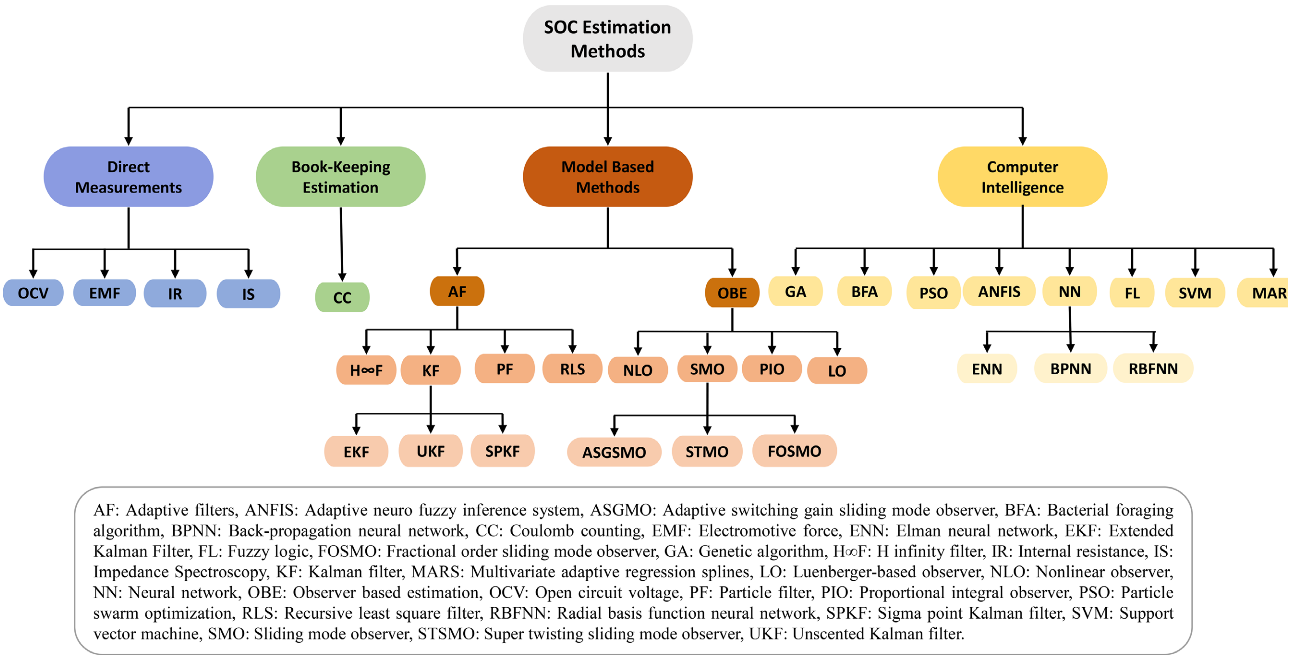

Figure 4. Classification of SOC estimation methods in modern BMS [34].

3.1. Battery Modeling Approaches

Battery modelling methods bring all-important abstractions of internal electrochemical behavior. They are usually divided into three categories:

- Electrochemical Models: Electrochemical models (EMs) take into account the ion diffusion and reaction kinetics with high accuracy and physical interpretability. Doyle-Fuller-Newman model, in particular, can be used in lab-scale simulations and in digital twin applications, but is computationally expensive and consequently not adaptable to onboard BMS hardware [1] [2].
- Equivalent Circuit Models: In commercial BMSs, Equivalent Circuit Models (ECMs) are preferred due to their viability in real-time and simplicity. They represent the battery as a parallel network of resistors, capacitors and voltage sources, frequently in Thevenin and or Dual Polarization forms [33]. Although less accurate than EMs, ECMs provide a good trade-off between SOC and SOH estimation in dynamic vehicle settings despite being not as precise as EMs [5]. ECM parameters are affected by temperature, C-rate, SOC, and aging. So online identification methods such as recursive least squares (RLS) and adaptive filtering are useful for real-time BMS applications [34].
- Data-Driven Models: Predictive models using data-driven methods are based

on historical battery data and can be trained with such methods as neural networks (NNs), long short-term memory (LSTM), and support vectors machines (SVMs). The models are particularly fruitful when it comes to managing nonlinear behavior as well as degradation patterns with time [1] [35] [36].

Battery modeling remains a fundamental trade-off between computational efficiency and electrochemical fidelity. Electrochemical models, especially the Doyle-Fuller-Newman (DFN) model, offer good physical interpretability but are too computationally expensive to be implemented on-board. Equivalent Circuit Models (ECMs) are therefore the most widely used solution in industry, as they offer good estimation accuracy and meet real-time computational constraints. The performance of the ECM, however, becomes poor under aging, temperature variation and dynamic loading unless the parameters are continuously updated by adaptive identification techniques like recursive least squares or Kalman filtering. Safety certification of recent deep learning approaches is difficult due to the need for large, high-quality datasets and the lack of interpretability in most cases when operating under nonlinear conditions. Thus, hybrid approaches, which integrate physics-based models with machine learning, are currently the most promising approach, as they leverage the complementary strengths of both approaches.

3.2. State Estimation Techniques

Safe and effective operation of battery packs in dynamic conditions is guaranteed by accurate state estimation. SOC estimation methods are commonly grouped into conventional methods, adaptive filtering algorithms, learning algorithms, nonlinear observers, and hybrid methods [34]. **Figure 5** represents a functional

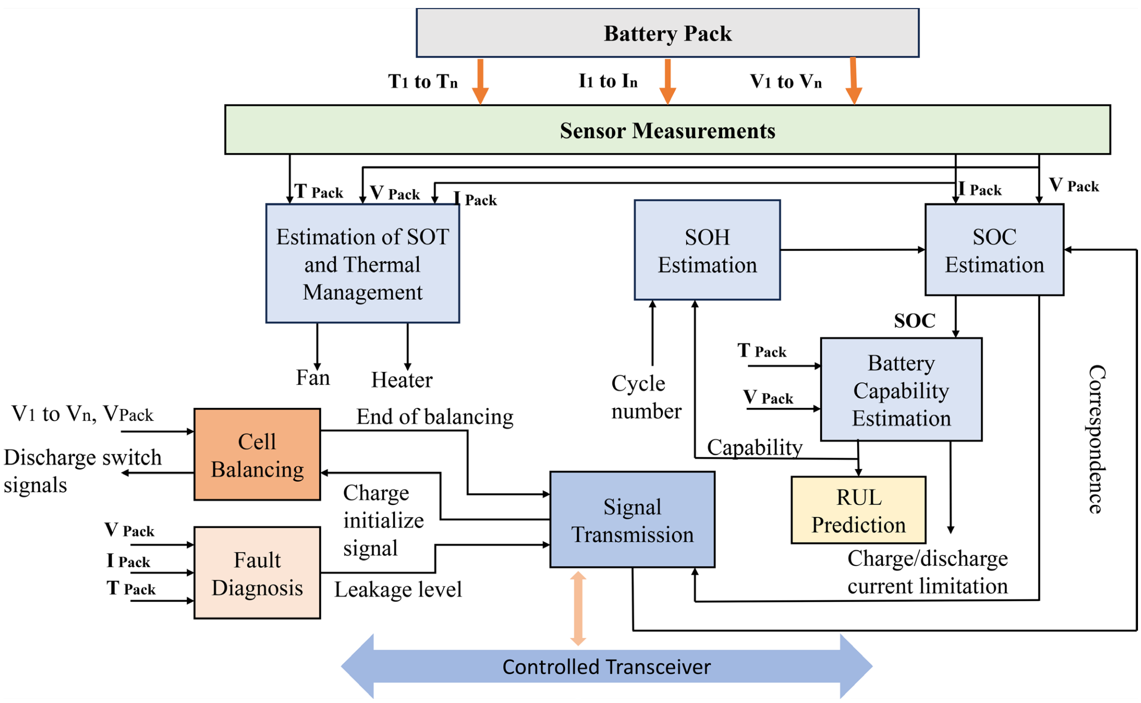

Figure 5. Functional block diagram of BMS for Evs [1].

block diagram of BMS for EVs, focusing on thermal parameter estimation, cell balancing and fault diagnosis.

3.2.1. Direct Estimation Methods

Direct techniques, including open-circuit voltage (OCV) look-up tables are computationally easy to use and provide a look-up table, but are influenced by hysteresis and temperature changes, which restricts their use in dynamic driving modes [5]. Ampere-hour counting is simple, has low cost but suffers from accumulated errors due to unknown initial SOC, capacity fading, self-discharge, and current sensor errors [34].

3.2.2. Model-Based Estimation Methods

Model-based approaches combine mathematical battery models with estimation algorithms. The filter-based processes and observer-based processes strive toward increased integrity and enhanced resilience. They rely heavily on the accuracy of the models involved and at a very high cost of computation. Examples include:

- Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF): These are suitable in the case of nonlinear dynamics, and are common in estimations in automotive SOC applications [2] [33].
- Particle Filters (PF): Offer good robustness to the uncertain systems, but require a high number of computational resources.
- Observers: Observers which include the Leuenberger and the H -infinity observers, provide stability in the presence of parameter uncertainty [1] [37].

3.2.3. AI-Based Estimation

AI-enhanced models especially those based on deep learning enable sophisticated pattern recognition from sensor streams. [38] presented a time-delayed RNN that was able to predict SOC with preciseness through various operational states. Such techniques facilitate diagnostics and degradation forecasting in real time, but require a lot of data quality and quantity.

3.3. Multi-Model Co-Estimation and Hybrid Frameworks

The multi-model co-estimation techniques are hybrid frameworks that combine ECMs, the electrochemical models, and AI-determined predictors. Such composite methodology increases both precision and strength at varying loads and temperatures [1] [33]. A summary of the advantages, limitations and use cases of the various state estimation methods is shown in **Table 1**.

The accuracy of estimation is a common metric to compare battery models. However, for the practical implementation of BMS, the robustness, computational efficiency, availability of training-data and validation conditions should be taken into account simultaneously. Electrochemical models are usually the most physically accurate, but require substantial computational resources and therefore are mostly used for offline simulation and digital twins. The equivalent circuit models are the preferred industrial solutions because they are computationally simpler

Table 1. Summary of modeling and estimation techniques.

Method Type	Advantages	Limitations	Use Cases
Electrochemical Models	High accuracy, physics-grounded.	High computation, not real-time suitable	Digital twins, offline simulation.
Equivalent Circuit Models (ECM)	Simple, fast, suitable for embedded use	Reduced accuracy, lacks internal detail	SOC/SOH tracking in BMS
Data-Driven Models	Flexible, handles nonlinear behavior	Needs large data, low interpretability	Predictive maintenance, AI-based BMS
Direct Estimation (OCV, empirical)	Fast, minimal processing	Inaccurate under dynamic loads	Basic BMS, low-end devices
Model-Based Estimation (EKF, PF)	Reliable in noise-prone environments	Moderate to high computational cost	Embedded EV systems
Multi-Model Co-Estimation	Robust, accurate, adaptive	Integration complexity	Advanced EVs, V2G, cloud-BMS integration

and have excellent real-time capabilities despite moderate reduction in estimation accuracy. After training with large data sets, deep learning models and other data-driven models tend to yield more accurate estimates under nonlinear operating conditions. Their performance, however, is very sensitive to the quality, diversity and representativeness of training data sets and many validated studies reported remain limited to laboratory environments. Thus, the most practical compromise among estimation accuracy, robustness, computational efficiency and deployment feasibility at the current time is to couple physics-based models with machine-learning algorithms in a hybrid estimation framework.

3.4. Challenges and Research Gaps

Several challenges remain despite significant progress. These include; sensor drift and data noise which degrades long-term model fidelity, overfitting of AI models and lack of explainability, real-time execution limits on embedded processors, lack of standardization for co-estimation frameworks among others.

Future trends involve federated learning to facilitate BMS optimization, graph neural networks (GNNs), to model thermo-electrical processes, and cyber-physical system (CPS) in digital twin [36] [38].

4. Battery Safety, Fault Diagnosis, and Standards

4.1. Key Safety Functions: Overcharge, Short-Circuit, Thermal Runaway Control

One of the most important functions of a Battery Management System (BMS) is safety management. Short circuiting, over-discharge, overcharge, and thermal runaway are some of the hazards that lithium-ion batteries possess and may lead to fire or explosion. BMS units avert this by using control logic to disconnect the battery in the overvoltage or overcurrent conditions and to activate thermal control mechanisms when the numbers reach hazardous levels [1] [5].

Generally, the optimal operating temperature range of the lithium- ion battery is 15˚C - 35˚C [39] [40]. Nevertheless, the temperature change in batteries is normally hard to circumvent since it is influenced by environmental conditions and heat dissipation during the charging and discharging process [41].

Specifically, temperature runaway incidents are controlled by early detection of temperature spikes, by isolating and shutting down or opening emergency discharge or cooling procedures to prevent chain reactions [33].

4.2. Fault Diagnosis: Data-Driven vs Model-Based Approaches

Model-based fault diagnosis is based on physics-based or circuit-based that uncover changes in anticipated behavior whereas data-driven diagnosis involves techniques using AI, such as support vector machines or neural networks, to analyze patterns in voltage, current, or temperature to detect anomalies [1] [38]. Although model-based techniques are intuitive and based on physical ideas, data-driven fault diagnosis methods have been shown to be more effective in detecting incipient and nonlinear faults under laboratory-validated conditions where sufficient labeled fault data exists [14] and are physically interpretable and well-suited for systems with well characterized battery dynamics. However, they are still under investigation for their ability to generalize to unseen operating conditions.

4.3. Industrial and International Standards

There are numerous criteria of BMS design and safety compliance, these include:

- IEC 61508: Functional safety of electronic systems.
- ISO 6469: Safety specifications for on-board rechargeable energy storage.
- SAE J2464, J2929: Test procedures for electric vehicle battery abuse.
- UL 1973/UL 9540: Performance and safety for stationary/vehicular batteries.
- GB 44240-2024: A Chinese regulation that governs lithium-ion batteries used in power energy storage systems, emphasizing thermal management and electrical safety.
- GB 38031-2020: China strengthened battery-system safety by adding thermal runaway/thermal propagation tests and requiring the BMS to detect thermal runaway and issue an alarm in time.
- GB 38031-2025: An updated mandatory national standard on the safety of electric vehicle batteries in China which took effect on July 1, 2026.

These standards regulate mandatory functions such as overcharge protection, temperature cutoff, short-circuit detection, and isolation control [33] [42].

4.4. Large-Scale and Vehicle-Based Systems Safety and Compliance

System level safety compliance considers the incorporation of fault tolerant mechanisms throughout the battery packs, modules and vehicle electronics. These are achieved by redundant communication protocols, distributed thermal sensing, and high-speed relays in large-scale systems to avert system depth failure [33].

Battery safety standards should be considered at multiple levels: materials, cell, module, battery system, BMS, and vehicle level [43]. A modular master-slave BMS topology demonstrated in **Figure 6** reduces wiring complexity and improves scalability for large battery packs enhancing safety.

Battery safety has developed from cell level protection to system level functional safety. While the previous BMS designs were mainly based on voltage and current limits, the new standards are more concerned with preventing thermal propagation, early fault diagnosis, and redundancy across the battery system.

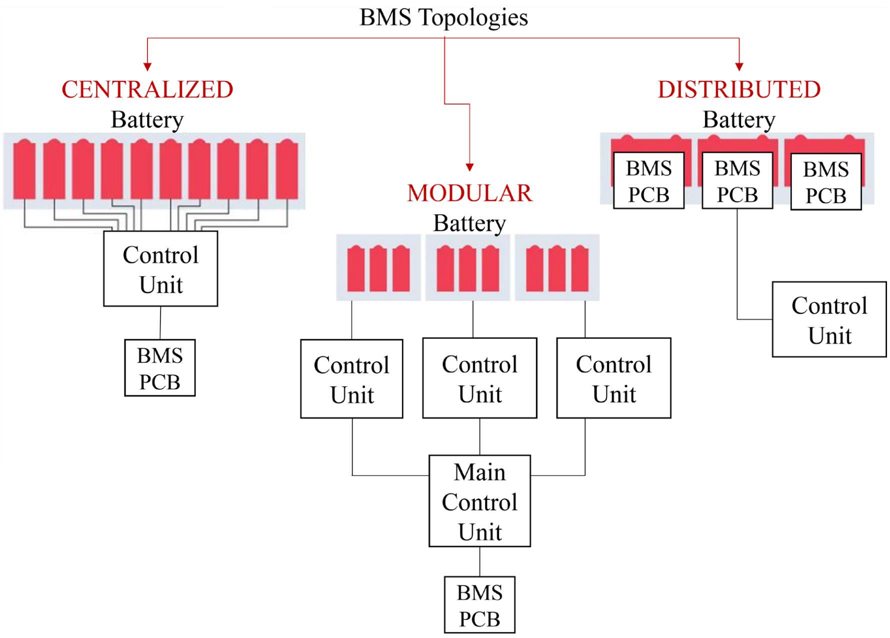

Figure 6. Master-slave architecture of BMS [33].

5. Cell Balancing Technologies

5.1. Passive Balancing (Resistive Methods)

Passive balancing techniques use resistors to dissipate excess charge from higher SOC cells as heat. Though simple and cost-effective, this method leads to energy loss and thermal management concerns. It is widely used in low-cost EVs and small-scale systems [1].

5.2. Active Balancing: Capacitor, Inductor, and Converter-Based Designs

Active balancing is classified into capacitor-based, inductor/transformer-based, and converter-based methods. Capacitor methods are simpler but slower; converter-based methods offer better regulation but higher cost and complexity. The process of active balancing enhances energy efficiency because it balances charge with energy transfer circuits between cells [44]. Capacitive balancing uses capacitors to temporarily store and shift charge while inductive balancing engages transformers or flyback converters to shift energy between cells. However, DC-DC converter-based balancing offers fine control over balancing currents and timing. Active balancing lowers energy wastage but becomes complex and more costly [33].

5.3. Integration with BMS Circuits for Energy Optimization

The use of Balancing circuits in BMS microcontroller units (MCUs) is linked and synchronized with SOC estimation algorithms. State-of-the-art systems operate on balancing thresholds depending on cell impedance and aging characteristics and maximize the performance and life cycles [5]. Passive balancing is cheap and simple but has high power loss and long balancing time, while active balancing saves more energy and handles higher power [44].

6. Thermal Management and Electrothermal Modeling

6.1. Cooling Strategies

Effective thermal regulation is necessary to guarantee safety and performance. Common methods include:

- Air cooling: Cost-effective but limited in high-load scenarios.
- Liquid cooling: Offers higher thermal conductivity, common in EV packs.
- Phase change materials (PCM): Absorb heat through latent energy storage.
- Hybrid systems: Combine two or more methods for dynamic conditions.

Advanced BMSs trigger different strategies based on load and environmental conditions [1]. **Figure 7** compares common thermal management technologies used in EV battery packs. Liquid cooling provides superior heat dissipation, while PCM-based systems offer passive thermal buffering. The different thermal management strategies exhibit trade-offs between cost, complexity, and cooling efficiency.

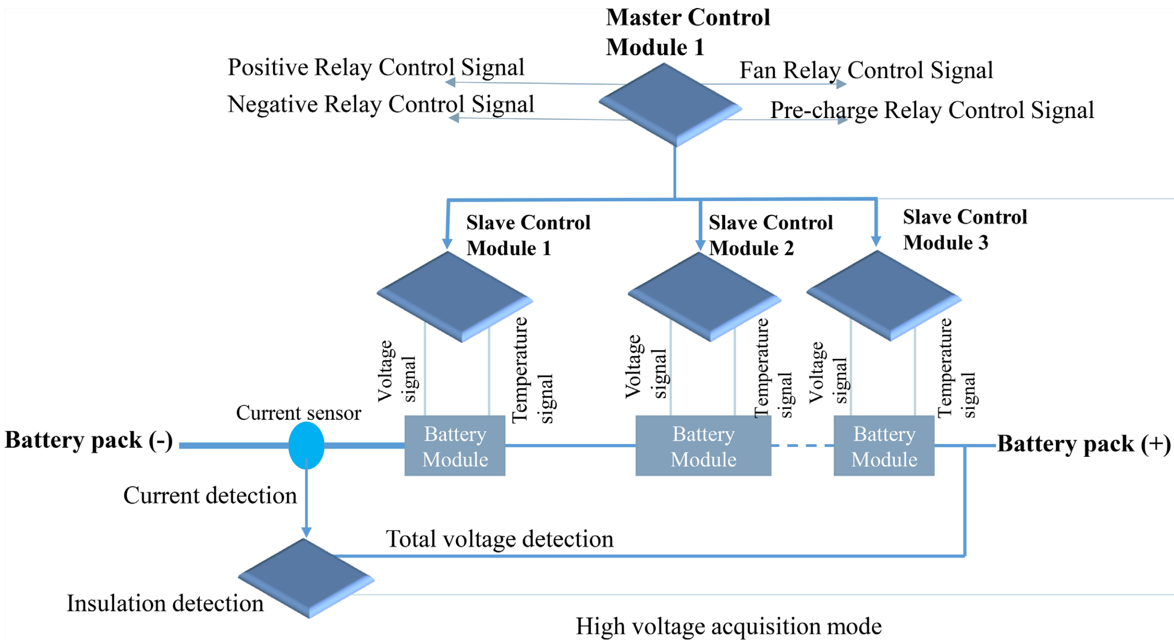

Figure 7. Thermal management methods for EV batteries.

Battery thermal management has shifted from maintaining average battery temperature toward controlling temperature uniformity throughout the battery pack. Although air cooling remains attractive because of its simplicity and low cost, its relatively poor heat transfer capability limits its suitability for high-energy-density battery systems. Liquid cooling is presently regarded as a preferred solution because of its proven effectiveness, and more importantly the technical feasibility of coupling with the integrated AC/HP system. The liquid BTMS can be further divided into the refrigerant-based system [45] and the coolant-based (e.g. water, glycol, oil, or acetone) system [46] [47]. PCM systems effectively absorb transient thermal loads but suffer from limited heat rejection capacity during prolonged operation. Consequently, recent studies increasingly advocate hybrid BTMS architectures that combine liquid cooling with PCM or heat pipes to exploit the advantages of multiple cooling mechanisms simultaneously.

6.2. Temperature Distribution Control in Packs

Uneven temperature distribution leads to cell aging, imbalance and reduced capacity. BMSs manage this through cell-level thermal sensors, cooling channel optimization, and predictive thermal models to distribute heat evenly during operation [33].

6.3. System-Level Thermal Optimization Techniques and Co-Simulation Models

Electro-thermal interactions on the system level are determined with the help of multi-physics simulation packages such as ANSYS or Simcenter. These maximize cooling design, sensor location and control strategy optimization. AI-driven digital twins are increasingly used to simulate and update thermal models in real time [38] [48].

7. Intelligent and Emerging BMS Technologies

7.1. AI and Machine Learning for Dynamic Management

Current BMS design has been revolutionized by AI into adaptive and predictive capabilities. Recurrent Neural Networks (RNNs) and Long Short-Term Memory networks (LSTMs) for state estimation [49], autoencoders for fault detection [50] [51], and federated learning for fleet-wide optimization. These models enhance accuracy in cases of uncertainty, fault detection, and real-time adjustments within a highly variable environment [36] [38]. AI has advanced as one of the fastest-growing research directions in battery management. Although deep neural networks are superior to traditional estimation algorithms in highly nonlinear operating conditions, their use in practice is limited by computational complexity, cybersecurity concerns, and lack of interpretability.

7.2. Blockchain, Cloud Computing, and Wireless Integration

Modern BMS hardware includes voltage/current/temperature sensing, impedance monitoring, protection circuits, communication transceivers and smoke/fault detection. BMS software uses sensor data for SOC/SOH estimation, control, diagnosis, and user-interface reporting. Therefore, BMS can be cloud-enabled to offload and store lifetime battery logs to be used in analytics. The blockchain protocols allow secure storage and tracking of battery transactions, which are essential in the second-life application and battery recycling networks [26] [35]. Wireless BMS (wBMS) decreases harness complexity and benefits modularity, but latency and signal loss should be considered [1]. They further enable fleet-wide optimization and predictive maintenance, but also pose communication latency, data privacy and functional safety certification challenges. Recent studies have shown that AI-based fault diagnosis can be more sensitive to fault detection than traditional model-based diagnosis, especially when trained on a large and representative dataset under different operating conditions and fault scenarios. However, where interpretability, physical consistency, and limited training data is needed, model-based approaches remain advantageous. Consequently, both approaches should be regarded as complementary rather than one being universally superior.

7.3. Move-and-Charge Systems and Real-Time Data Platforms

The future designs of BMS will be able to support dynamic charging during operation (e.g., inductive highways) and real-time exchange of data with grid systems. Content based on the digital twin, V2G implementation, and smart maintenance schedule management will form best practices in smart cities and business fleets.

8. Battery End-of-Life Management and Regulatory Constraints

Recent research has extensively explored second-life applications of lithium-ion batteries, where retired electric vehicle batteries are repurposed for stationary energy storage systems. These approaches aim to extend battery lifecycle and improve resource efficiency. Second-life battery utilization represents one of the most promising approaches for reducing battery lifecycle costs and supporting the circular economy.

However, regulatory frameworks differ significantly across regions. Recent Chinese regulations increasingly prioritize battery traceability and recycling over unrestricted second-life utilization, highlighting the importance of integrating regulatory requirements directly into BMS design rather than treating them as post-processing considerations, The policy developments impose strict constraints on cascade utilization of retired EV batteries. Batteries with a state of health below approximately 80% are typically classified as end-of-life and are directed toward recycling rather than reuse in secondary applications. This regulatory position is driven by several factors, including safety risks associated with aged cells, lack of standardized evaluation protocols for reuse, and challenges in lifecycle traceability. As a result, the practical implementation of second-life battery systems remains limited within the Chinese context.

Consequently, the focus of BMS development is shifting toward, accurate end-of-life diagnostics, lifecycle tracking and data transparency, and recycling-oriented system design. This transition highlights the growing importance of integrating policy compliance into technical BMS design, particularly for large-scale industrial deployment. BMS faces challenges such as battery disposal, limited data logging, heavy/costly circuitry, and inadequate prognostics comparison. Future BMS should improve data logging, prognostics, and lifecycle databases [44].

9. Challenges, Opportunities, and Future Directions

The future of battery management systems will not depend solely on improvements in individual estimation algorithms but rather on the successful integration of electrochemical modeling, artificial intelligence, cloud computing, digital twins, wireless communication, and lifecycle management into a unified cyber-physical ecosystem. Although considerable progress has been achieved, current BMS architectures remain fragmented, with independent solutions developed for state estimation, thermal management, balancing, and fault diagnosis. Future research should therefore prioritize holistic system integration, standardized communication protocols, explainable artificial intelligence, and scalable validation frameworks capable of supporting next-generation solid-state batteries and intelligent connected vehicles.

9.1. Technical Gaps

A number of barriers to performance currently exist in the BMS sector. These include:

- Fast-charging safety: Where high current during rapid charging increases temperature and lithium plating risks.
- Miniaturization: The occurrence where onboard BMS hardware remains bulky relative to embedded AI goals.
- Latency in protection circuits: Current relay or fuse-based systems having finite delay which may cause failure under sudden shorts.

These limitations require the enhancement of real-time diagnostics, solid-state relay implementation, and failure anticipated analytics [33].

9.2. Research Opportunities: Integrated Sensing, Cyber-Physical Modeling and Solid-State BMS

Development of solid-state batteries (SSBs) introduces new challenges for BMS such as the lack of liquid electrolyte eliminating standard thermal paths and interface degradation which is hard to detect using conventional impedance methods. BMS research must focus on embedded flexible sensors, non-contact temperature/strain monitors, and cyber-physical modeling, combining real-time signals with virtual twin simulations [38] [48], as well as federated learning which has the possibility of cross-fleet optimization without violating data privacy.

9.3. Industrial Alignment and Policies for Scalable Implementation

To ensure that the adoption of BMS innovation is universal, there must be regulatory, industrial, and commercial alignment. Currently, the lack of international BMS communication standards, inconsistent recycling regulations across regions and proprietary data formats limiting interoperability are a few challenges being faced. Recent advancements like the Battery Passport by the EU and the traceability laws of China are pointing to transparency of data, EoL reporting and green design certifications [35].

10. Conclusions

BMS have evolved from basic protection circuits to intelligent cyber-physical platforms that incorporate sensing, estimation, thermal control, diagnostics, communication, and lifecycle management. This review has exhibited that recent advances in battery modeling, artificial intelligence, cloud computing, digital twins, and wireless communication are fundamentally modifying battery management for new energy vehicles. While electrochemical and equivalent circuit models continue to provide the foundation for state estimation, hybrid models that integrate physics-based models with machine learning are becoming more popular as they provide the best compromise between computational efficiency, estimation accuracy, and adaptability to dynamic operating conditions.

The review also points out that BMS development extends beyond battery performance optimization. BMS must not only ensure operational safety, but also track battery life, predict failures, and comply with regulations, all of which are becoming more stringent. These budding requirements call for closer integration between hardware design, embedded intelligence, cloud computing, and policy frameworks.

Despite substantial progress, there are still a number of scientific and engineering issues that have not been addressed. These include strong multi-state estimation under aging and uncertain operating conditions, explainable artificial intelligence for safety-critical applications, standardized validation of intelligent BMS algorithms, chemistry-specific management strategies for next generation batteries, and seamless integration of electrochemical, thermal and mechanical models into real-time digital twin frameworks. Tackling these challenges will require interdisciplinary collaboration between battery scientists, control engineers, data scientists, automotive manufacturers, and regulatory agencies.

In general, the development of Battery Management Systems is progressing towards intelligent, connected and self-adaptive platforms that can enable safer, more efficient and more sustainable electric transportation. The widespread use of next-generation new energy vehicles will be greatly promoted by the continuous development of cyber-physical integration, predictive analysis, and standardized intelligent control.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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