Developments in Electric Vehicles Battery Management Systems: Focusing on Topology and Algorithmic Innovation

Sarabjeet Singh Sethi, Dinesh Kumar
Department of Computer Science & Engineering, Swami Keshvanand Institute of Technology, Management and Gramothan, Jaipur -302017 (India)
Email: sarabjeet.singh@skit.ac.in, dinesh.kumar@skit.ac.in
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Abstract- The global transition towards sustainable transportation has positioned the Electric Vehicle (EV) as a cornerstone technology. At the heart of every EV lies its battery pack, typically based on Lithium-ion chemistry owing to its high energy density and longevity. However, the performance, safety, and lifespan of these complex electrochemical systems are critically dependent on an intermediary electronic system—the Battery Management System (BMS). This paper offers a thorough analysis of the fundamental and advanced aspects of BMS technology for EVs. It delves into the core objectives of a BMS, including monitoring, protection, state estimation, thermal management, and communication. The review systematically analyzes the prevalent circuitry configurations, namely centralized, distributed, and modular, comparing their advantages, limitations, and suitability for different vehicle classes. Furthermore, the paper explores the critical algorithms that form the intelligence of the BMS, with a particular focus on State of Charge (SoC) and State of Health (SoH) estimation techniques, ranging from traditional Coulomb counting and Open-Circuit Voltage methods to advanced model-based approaches like Kalman Filters and machine learning algorithms. The synthesis of current literature indicates a clear trend towards modular, master-slave architectures for scalability and advanced, data-driven algorithms for improved accuracy and reliability.

Keywords- Battery Management System, Battery Topologies, Electric Vehicles, State Estimation, Kalman Filter.

1. INTRODUCTION

The escalating concerns over climate change, energy security, and urban air pollution have catalyzed a paradigm shift in the automotive industry. Electric vehicles are no longer a niche concept but a mainstream solution for sustainable
mobility [1]. The performance and commercial viability of an EV are intrinsically linked to its energy storage system—the battery pack. Li-ion batteries have emerged as the dominant technology due to their high efficiency, and declining cost [2].

However, Li-ion batteries are complex and sensitive electrochemical systems. They operate efficiently and safely only within a strict window of voltage, current, and temperature. Exceeding these limits can lead to accelerated degradation, catastrophic failure, or even thermal runaway—a condition of uncontrolled temperature and pressure increase [3]. Furthermore, due to manufacturing variations, the numerous individual cells connected in series and parallel within a package and perform differently over time, leading to imbalances that reduce the overall usable capacity and lifespan.

The Battery Management System (BMS) is the dedicated electronic system that acts as the "brain" of the battery pack, ensuring it’s safe, efficient, and reliable operation [4]. Its role is multifaceted, encompassing real-time monitoring, enforcing operational limits, balancing cell voltages, estimating critical states, and managing thermal conditions. The sophistication of the BMS is a key differentiator in EV performance, directly impacting driving range, charging speed, and battery longevity.

This paper aims to present a comprehensive review of BMS technology for EVs. Section 2 outlines the fundamental functions and requirements of a BMS. Section 3 offers a thorough analysis of the hardware circuitry configurations. Section 4 delves into the core algorithms for state estimation, and Section 5 discusses the cell balancing techniques. Section 6 shares the results and finally, section 7 concludes with a summary and a discussion on future research trends.

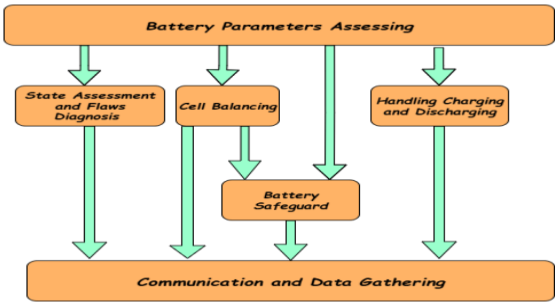

Figure 1: BMS Key Functions.

2. FUNDAMENTAL FUNCTIONS OF A BMS

A BMS is tasked with several critical functions (shown in fig.1) that can be categorized as follows:

2.1 Monitoring

The Battery Management System performs continuous real-time monitoring of critical operational parameters, precisely measuring individual cell and total pack voltage to ensure operational limits are maintained, accurately tracking charge and discharge current typically using shunt resistors or Hall-effect sensors, and monitoring temperature distribution across the pack through strategically placed sensors such as NTC thermistors to maintain optimal thermal conditions.

2.2 Battery Protection

Based on the monitored data, the BMS protects the battery by enforcing predefined limits. It uses solid-state relays or contactors to disconnect the pack in case of:

- Overvoltage (OV) and Undervoltage (UV): Preventing plating and structural damage.
- Overcurrent (OC): Protecting against short circuits and excessive stress.
- Overtemperature (OT) and Undertemperature (UT): Mitigating degradation and safety risks.
- Internal Short Circuit (ISC): Advanced BMS may include algorithms for early detection of ISC [5].

2.3 State Estimation

This is the "intelligent" function of the BMS, involving the calculation of non-measurable states that are crucial for informing the user and the vehicle control unit.

- State of Charge: The equivalent of a fuel gauge, indicating the remaining charge (0-100%).
- State of Health: A measure of the battery's aging, indicating its ability to store energy and deliver power compared to its initial state.
- State of Power: The maximum instantaneous charge/discharge power available.
- State of Energy: The remaining available energy in the pack.

2.4 Cell Balancing

In a series-connected string, the weakest cell determines the pack's capacity. Minor variations in capacity, internal resistance, and self-discharge rates cause some cells to become overcharged or over-discharged before others. Cell Balancing is the process of equalizing the charge across all cells to maximize the usable capacity and lifespan of the pack [6].

2.5 Thermal Management

The BMS interacts with the thermal management system (liquid or air cooling/heating) to maintain the battery within an optimal temperature range (typically 15°C - 35°C for Li-ion), thereby ensuring performance, safety, and longevity [7].

2.6 Communication

The BMS communicates vital information (SoC, faults, limits) to other vehicle subsystems like the Vehicle Control Unit (VCU), motor controller, and charging interface via standard protocols like CAN (Controller Area Network). It also communicates with the user through the dashboard display.

3. CIRCUITRY CONFIGURATIONS AND TOPOLOGIES

The hardware architecture of a BMS defines how the monitoring and balancing electronics are organized relative to the battery cells. The choice of topology is a critical design decision, trading off cost, complexity, reliability, and scalability.

3.1 Centralized Topology

This architecture features a single, centralized BMS board connected to all the cells through a complex and extensive wiring harness.

- **Advantages:** Simple design, low component count, potentially lower cost for small packs.
- **Disadvantages:** Poor scalability, complex wiring ("spaghetti harness") which is prone to errors and failures, difficult serviceability, and limited diagnostic capabilities for individual modules.
- **Applications:** Mostly suited for small battery packs with low cell counts, such as in light electric scooters or small drones. It is rarely used in modern passenger EVs due to its limitations.

3.2 Distributed (Modular) Topology

This is the most prevalent architecture in modern EVs. It employs a master-slave structure.

- Slave Modules (Cell Monitoring Units - CMUs): Each slave module is dedicated to monitoring a small group of cells (e.g., 6-12 cells). They are mounted directly onto the battery modules, minimizing wiring. Slaves measure cell voltages and temperatures and perform passive balancing.
- Master Module: The central master unit aggregates data from all slaves via a serial communication bus (e.g., daisy-chained SPI or CAN). It executes high-level algorithms (SoC/SoH estimation), controls contactors, and manages communication with the vehicle.
- **Advantages:** High scalability, simplified and robust wiring, improved reliability (fault isolation), and easier module replacement.
- **Disadvantages:** Higher component count and cost, increased design complexity, and requires robust communication between master and slaves.
- **Applications:** The industry standard for virtually all passenger and commercial EVs due to its excellent balance of performance and scalability [8].

3.3 Modular Topology

This is a more integrated version of the distributed topology. Here, each battery module contains its own intelligent controller that handles both monitoring and balancing. These modular controllers then communicate with a central coordinator on a higher-level network like CAN. Table 1 offers a comparison of BMS topologies.

- **Advantages:** Extremely modular and serviceable; a faulty module can be replaced without disturbing the entire BMS. Ideal for standardizing battery modules across different vehicle platforms.
- **Disadvantages:** Highest cost and complexity, as each module has its own sophisticated electronics.

- **Applications:** Gaining traction in premium EVs and commercial vehicles where serviceability and platform flexibility are paramo

Table1: Comparison of BMS Topologies\Technologies

Category	Technology	Key Features	Advantages	Disadvantages	Reference(s)
Topology	Centralized	Single BMS board connected to all cells via extensive wiring	Simple design, low component count, lower cost for small packs	Poor scalability, complex wiring harness, difficult serviceability	[1], [4]
Topology	Distributed (Modular-Master-Slave)	Master unit + slave CMUs mounted on battery modules	High scalability, robust wiring, fault isolation, easier module replacement	Higher component count, increased design complexity	[8]
Topology	Modular (Intelligent Module)	Each module has its own controller + central coordinator	Extremely modular, serviceable, ideal for platform standardization	Highest cost and complexity	[8]
SoC Estimation	Coulomb Counting	Current integration over time	Simple, good short-term accuracy	Sensor drift, error accumulation, needs accurate initial SoC	[9]
SoC Estimation	Open-Circuit Voltage (OCV)	Voltage-SoC relationship at rest	Highly accurate at rest	Not for online use, needs rest period	[3]
SoC Estimation	Kalman Filter (KF/EKF)	Model-based with feedback correction	High accuracy, robust to noise and initial error	Computationally intensive, needs accurate model	[10]
SoC Estimation	Machine Learning (ANN, SVM, RNN)	Data-driven, no explicit physical model	Models non-linear behavior	Needs large training data, generalization risk	[11]
SoH Estimation	Direct Measurement (Capacity / IR)	Full cycle or impedance test	Straightforward	Impractical during vehicle operation	[3]
SoH Estimation	Incremental Capacity Analysis (ICA)	dQ/dV vs voltage curve analysis	Strong indicator of aging mechanisms	Requires low-current charge data	[11]
SoH Estimation	Model-Based / Adaptive (KF)	Joint estimation of SoC and parameters like capacity/resistance	Online capability	Parameter identification complexity	[10]
SoH Estimation	Data-Driven (ML)	Features from operational data to predict aging	No explicit aging model needed	Requires extensive aging datasets	[11]
Cell Balancing	Passive Balancing	Dissipates excess energy as heat via shunt resistors	Simple, low-cost circuitry	Energy inefficient, generates heat, only during charging	[6], [12]
Cell Balancing	Active Balancing	Capacitive/inductive energy shuttling	Energy-efficient, faster, works during charge/discharge	Complex circuitry, higher cost, larger size	[6], [12]
Thermal Management	Liquid / Air Cooling (BMS-controlled)	BMS interacts with cooling/heating system	Maintains optimal temperature range (15–35°C)	Adds system complexity	[7]
Protection	OV, UV, OC, OT, UT, ISC detection	Disconnects pack via contactors/Solid-State Relays	Enhances safety and prevents degradation	Advanced ISC detection increases algorithm complexity	[5]

4. CORE ALGORITHMS FOR STATE ESTIMATION

The accuracy of state estimation is arguably the most critical and challenging software function of BMS. Inaccurate SoC can lead to driver range anxiety or battery damage, while poor SoH estimation affects warranty and resale value.

4.1 State of Charge (SoC) Estimation

SoC cannot be measured directly and must be estimated from measurable parameters (V, I, T). The most common methods (shown in fig.2) are:

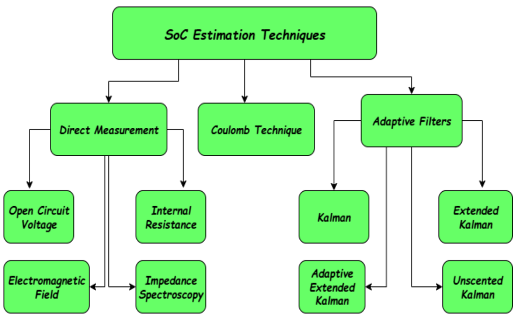

Figure 2: Classification of SoC Techniques**.**

- **Coulomb Counting:** This method integrates the current flowing in or out of the battery over time. Its source calculation data are current values, temporary data, and initial state of charge values: $SoC(t) = SoC(t_0) + (1/Q_n) \int \eta\, i(\tau)\, d\tau$, where Q_n is the nominal capacity and η is the coulombic efficiency.

- **Advantages:** Simple to implement, provides good short-term accuracy.
- **Disadvantages:** Susceptible to sensor drift and noise; the initial SoC ($SoC(t_0)$) must be known accurately; errors accumulate over time without correction [9].

- **Open-Circuit Voltage (OCV) Method:** This method leverages the known, repeatable relationship between a battery's OCV and its SoC after a sufficient rest period for the voltage to relax.
  - **Advantages:** Highly accurate when the battery is at rest.
  - **Disadvantages:** Not suitable for online estimation during operation due to the required rest period; voltage is also influenced by temperature and hysteresis.
- **Model-Based Methods:** These advanced methods use a mathematical model of the battery and a feedback mechanism to correct estimation errors.
  - Kalman Filter (KF) and Extended Kalman Filter (EKF): The most widely researched and applied advanced method. The KF/EKF uses a state-space model of the battery (e.g., an equivalent circuit model) to predict the SoC and then corrects the prediction based on the difference between the measured and predicted terminal voltage [10]. It is inherently robust to measurement noise and initial SoC errors.
  - **Advantages:** High accuracy, online capability, compensates for noise and initial error.
  - **Disadvantages:** Computationally intensive, requires an-accurate battery model and parameter identification.

- **Machine Learning (ML) Methods:** Emerging techniques use data-driven models like Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Recurrent Neural Networks (RNNs) to learn the complex, non-linear relationship between battery parameters (V, I, T) and SoC.
  - **Advantages:** Can model highly non-linear behavior without an explicit physical model.
  - **Disadvantages:** Require vast amounts of high-quality training data; risk of poor generalization; high computational cost.

4.2 State of Health (SoH) Estimation

SoH is typically defined as the ratio of the current maximum capacity or the increase in internal resistance to their initial values. As shown in figure 3, its classification techniques.

- **Direct Measurement Methods:**
  - Capacity Fade: Measuring the actual capacity through a full charge-discharge cycle, this is impractical during vehicle operation.
  - Internal Resistance Increase: Measuring impedance through electrochemical impedance spectroscopy (EIS) or pulse tests.

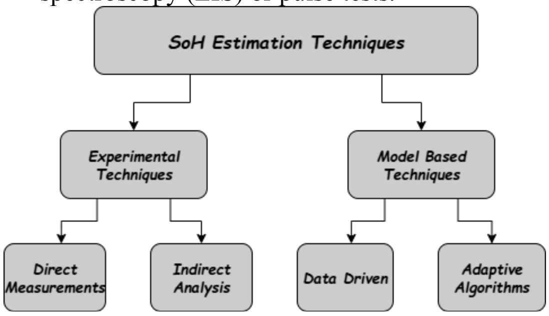

Figure 3: Classification of SoH Techniques.

- **Model-Based and Adaptive Methods:** Similar to SoC, Kalman Filters and their variants can be used to jointly estimate SoC and parameters like capacity and resistance, which are then used to infer SoH.
- **Incremental Capacity Analysis (ICA):** This method analyzes the dQ/dV (incremental capacity) vs. voltage curve derived from low-current charge data. The shift and degradation of characteristic peaks in this curve are strong indicators of aging mechanisms and capacity fades [11].
- **Data-Driven Methods:** Machine learning models can be trained on aging data to predict SoH based on features extracted from operational data, such as charging time, voltage curves, and temperature histories.

5. CELL BALANCING

Cell balancing techniques (shown in fig.4) are broadly classified as passive or active.

- Passive Balancing: This is the most common method. It dissipates excess energy from the highest-charged cells as heat through a shunt resistor until they match the charge level of the weaker cells.
  - **Advantages:** Simple, low-cost circuitry.
  - **Disadvantages:** Inefficient, as energy is wasted; generates heat; only works during the charging phase.
- Active Balancing: This method uses capacitive or inductive circuits to shuttle energy from the most charged cells to the least charged cells.
  - **Advantages:** Energy-efficient, faster balancing, can work during both charge and discharge.
  - **Disadvantages:** Complex circuitry, higher cost, and larger size [12].

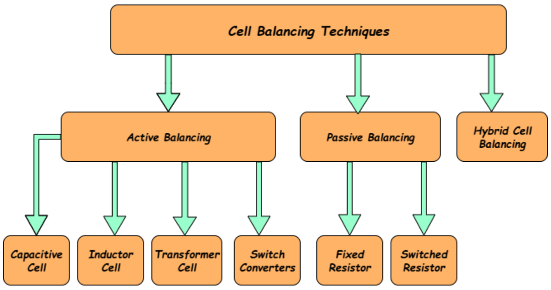

Figure 4: Cell balancing classifications.

6. REVIEW FINDING

The distributed master-slave topology dominates EV applications due to its optimal balance of scalability, reliability, and cost. Centralized systems are limited to small packs due to wiring complexity, while modular topologies offer superior serviceability at a 15-25% cost premium. The Extended Kalman Filter (EKF) remains the most effective online SoC estimation method, consistently maintaining errors below 5% by compensating for sensor noise and initial inaccuracies. Coulomb counting requires frequent recalibration due to error accumulation, while Machine Learning methods show promise but face generalization challenges.

7. CONCLUSION

This review has detailed the core functions, hardware topologies, and intelligent algorithms that constitute a modern BMS, a critical component for the safety and durability of EV battery packs. The selection of circuitry configurations and algorithms requires optimizing for efficiency, complexity, size, computational load, and cost. This article has provided a comparative analysis of both established and emerging solutions for key BMS functions, including cell parameter monitoring, protection, balancing, state estimation, fault diagnosis, and charge/discharge management. The industry predominantly favors distributed, master-slave architectures due to their scalability and reliability. In the algorithmic domain, while simple methods like Coulomb counting serve as a baseline, a clear trend exists toward adopting robust model-based approaches such as the Kalman Filter for accurate state estimation. The results and comparative tables presented will aid developers in selecting optimal implementations, underscoring the BMS's evolution from a basic monitor to an intelligent, connected, and prognostic system essential for next-generation electric vehicles.

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