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PERFORMANCE EVALUATION OF BATTERY MANAGEMENT SYSTEMS IN LITHIUM-ION BATTERY-POWERED ELECTRIC VEHICLES

Basit Azam [1], Sanam Mehar [2]

Affiliations

[1] Master in Electrical Power Engineering
Glasgow Caledonian University
Scotland, UK
bazam1345@gmail.com

[2] Department of Electrical, Electronics and Telecommunication Engineering and Naval Architecture (DITEN),
University of Genova, Italy
sanam.mehar@edu.unige.it

Corresponding Author's Email

[1] bazam1345@gmail.com

ABSTRACT

This work provides the first exhaustive quantitative assessment of Battery Management Systems (BMS) in electric vehicles (EVs). This work evaluates BMS as each attempts to establish the State of Charge (SOC) and State of Health (SOH) estimation, cell balancing, thermal control, and fault safeguarding efficiency. This work evaluates real-world scenario BMS efficiency considering different driving conditions, environmental conditions, and scenarios to age the battery pack. A substantial amount of work has been done to assess the battery pack's cell voltages, currents, temperatures, State of Charge/State of Health, and fault logs in a 48V, 60Ah lithium-ion battery pack. The work has primarily focused on measuring the SOC error, SOH drift, balancing efficiency, and thermal deviation. This work demonstrates the BMS SOC estimation efficiency of 3% error, while SOH estimation accuracy dropped by 5% after 1000 cycles of charge and discharge. BMS cell balancing works efficiently at average driving conditions; however, it becomes much less efficient with aggressive driving. The BMS thermal regulation suffered greatly in extreme heat (45°C) as the temperature regulation control was ±5°C from the ideal temperature of 5°C. Fault BMS fault detection was remarkably fast, detecting overvoltage and overcurrent conditions in less than 200 ms. This work provides a summary of important BMS efficiency bottlenecks while offering solutions to advance BMS safety, BMS longevity, and BMS powered EVs efficiency.

Keywords: Battery Management System (BMS), State of Charge (SOC), State of Health (SOH), Cell Balancing, Thermal Regulation

INTRODUCTION

A. Background

Lithium-ion (Li-ion) batteries offer the best energy density, cycle life, and self-discharge rates, and thus, it is the most important battery technology for the electric vehicles (EVs) market. EVs use Li-ion batteries to power the electric core motors without surpassing the weight and cost limits of the vehicle. The automotive sector emphasizes the optimization of battery technology for completing the final elements of a vehicle battery, as sustainability and energy efficiency become fundamental to automotive manufacturing. But still the efficient use of lithium-ion batteries in EVs primarily depends on the sophisticated technology embedded in the battery Management System (BMS). The BMS ensures the safe, reliable and efficient use of Li-ion batteries and battery packs in an EV. Some of the other sophisticated BMS functions include: assessing battery "health" and state of charge for every cell and battery pack, protecting against overcharge and deep discharge, thermal runaway, cell imbalance and age. Finally, active and passive thermal control is vital to ensuring battery pack life and safety. Excessive heat pose a battery life cycle and safety risk. It is the BMS that facilitates the safe use of Li-ion batteries in EVs.

In light of the above BMS focus it will guarantee the battery functions safely and extends the battery lifespan and functions optimally under various working conditions. How a BMS functions will impact the overall safety, effectiveness, and dependability of electric vehicles. A BMS that functions well will enhance a battery performance to ensure a vehicle meets its intended range and also prevents battery safety risks. Assessing performance of battery management systems will shed light on the understanding of BMS capabilities in the real world and identification of potential improvements that may be translated to better vehicle performance and improved user experience.

B. Problem Statement

Even BMS fundamental functions still face challenges in the management and optimization operations of an EV battery system. The estimation of battery pack state, particularly in state of charge (bank) and state of health, is the most significant challenge. The state of charge is the battery energy remaining, while the state of health represents the age and condition of the battery in the pack. Estimating these metrics and determining the values accurately in battery optimization utilization, overuse prevention, battery depletion, and over deterioration is important. Several managed and unmanaged variables negatively impact estimation accuracy. These include age, temperature, and battery pack individual cells performance variability relative to deterioration. The variability in temperature and their range is especially important concerning battery performance, life and deterioration. Overheating is especially detrimental due to rapid deterioration, capacity reduction, and even thermal runaway at the pack. Within BMS, the battery thermal control system is responsible for maintaining a safe temperature range, particularly during fast charging periods and peak load periods.

Cell balancing remains another challenge. Imbalances arise when some battery pack member cells do not charge and discharge in a consistent fashion. Over time, some cells might overcharge while others discharge too much, leading to cell capacity lose and in some cases, battery pack failure. Imbalanced large battery cell packs becomes particularly difficult to manage in EV applications. Over time and especially in large packs, differences in cell characteristics and parameters may become exaggerated. In addition to such technical challenges, communication and control latency remains a challenge. The BMS handles real-time data and estimates control communication interfacing with the vehicle powertrain and other control systems for optimal performance, data communication latency, control response lags, and estimated performance gaps live in the system and may present inefficient, and in some cases, unsafe operational performance to the user. Despite challenges and issues, real-world evaluations of BMS performance remains unaddressed in the literature. For instance, while the SOC estimation accuracy and cell balancing efficiency have each seen independent performance focus in laboratory testing, studies integrating these performance metrics in battery evaluations have neglected the context of prolonged battery usage, disparate environmental, and varied automotive driving profiles. The influence of battery aging on the performance of the BMS has been the subject of relatively few studies, as has the extent to which varied cell chemistries affect the efficacy longevity of the BMS.

C. Objective

This study seeks to systematically evaluate the operational efficacy of battery management systems (BMS) in electric vehicles. We study effectiveness in real-life driving scenarios with an emphasis on BMS functions related to SOC/SOH estimation, cell balancing, thermal management, fault mitigation, and overall performance. These functions are evaluated in the study given various parameters of driving and battery aging to provide a range of strengths and weaknesses in the various BMS (battery management systems) technologies. This study evaluates extreme range ambient temperature as an additional environmental variable for an inter-facility comparison involving the relative merits of centralized and decentralized BMS systems. The findings are expected to enhance BMS design and improve the safety, efficiency, and operational life of electric vehicle batteries, thereby facilitating the widespread adoption of electric vehicles.

D. Scope of the Study

This research investigates battery management systems (BMS) dynamics both hardware and software that regulates lithium-ion battery packs utilized in electric vehicles (EVs). Evaluations of performance will look at multiple facets such as the precision of estimating the state of charge (SOC) and state of health (SOH), balancing of cells, management of pack temperature, detection and response to faults, and others. The research will endeavor to study the performance of BMS systems in the context of different driving behaviors, weather conditions, and battery decline. Exclusions will be the innovations in the batteries' chemistry and the motor and drive system power electronics, as long as they relate to BMS. While such systems are undeniably important concerning the performance of EVs, the main focus for this research will be the BMS and the control effectiveness of the BMS on the battery pack. The EV powertrain and charging subsystems will also not be included in this research, despite their importance to the overall performance of the EV.

E. Research Questions

- What is the accuracy and reliability of the BMS throughout the lifecycle of lithium-ion battery packs in EVs in estimating SOC and SOH?
- How well does the BMS perform cell balancing, thermal regulation, and fault protection under different operational conditions?
- How do battery aging, driving patterns, and environmental factors affect BMS operation?
- How do different BMS configurations, namely centralized and distributed, differ regarding real-world performance indicators?

F. Significance of the Study

This paper illustrates recent progress in relation to Electric Vehicles (EV) technologies, specifically, advancements in Battery Management Systems (BMS). More specifically, it provides empirical analyses on BMS in practice, through a combination of hands-on trials followed by data analyses. Evaluating BMS performance under varying driving conditions, extreme temperature ranges, and different aging conditions, provides a comprehensive understanding of the efficacy of BMS systems. Proposed in this study are recommendations aimed at safe and effective battery pack design, addressing battery pack longevity, and thereby serving the interests of EV manufacturers, BMS designers, and battery policy makers. He further attempts to bridge the gap between BMS theoretical knowledge and practical application, suggesting routes toward sophisticated practical utility and efficiency of BMS. The fundamental effect of this will be an improvement not only on the environmental impact of EVs, but also on their cost, and operational efficiency, by optimizing the BMS circuitry.

LITERATURE REVIEW

A. Overview of BMS in EVs

Battery Management Systems (BMS) are responsible for maintaining the performance, safety, and durability of lithium-ion batteries used in electric vehicles (EVs). A BMS performs monitoring, protection, cell balancing, state estimation, and thermal management. Monitoring keeps track of the batteries' voltage, current, and temperature on a continual basis, as well as ensuring that the defined limits are adhered to, thus assisting in the prevention of accelerated deterioration of batteries and avoiding safety issues related to batteries. Cell balancing guarantees that all cells within a battery pack share the same charge. Rapid wear and battery pack failure come from diminished battery pack capacities along unevenly over discharged and overcharged cells [1]. State estimation is crucial for a BMS to make a decision, most importantly the estimation for SOC and SOH.

SOC estimation indicates to a BMS how much charge a battery contains, while SOH estimation determines battery power delivery potential over a given time [2]. This estimation enables the BMS to predict battery behavior and battery life, optimal charging cycles, and harmful deep discharges that should be avoided. The BMS protective function limits the potential damages that the batteries may incur from extreme operational conditions such as overvoltage, undervoltage, extreme heat, and extreme cold. An example of a protective function would be throttling the charging and discharging rates of the batteries or disconnecting them altogether. The last of the core functions that a BMS must perform is maintaining a battery's system's thermal equilibrium. As a battery system is charged and discharged, it expands, overheating and potential thermal runaway can occur, which increases performance degradation, shortens the battery's lifespan, or increases the chance of safety issues. Therefore, it is important to dissipate and control a battery's heat to maintain it within safe limits [3]. A BMS can be centralized, modular, or distributed. Only one BMS manages all functions of a centralized system, which can simplify the system at the cost of creating a bottleneck. A modular system improves scalability and flexibility of the system by subdividing control responsibilities into smaller portions for autonomy over the battery system. However, this increases system complexity. In a distributed configuration, a BMS incorporates control units at each cell level. This approach provides the highest level of monitoring and control granularity, but it also necessitates intricate communication schemes and may lead to greater expenses and upkeep. Each configuration or architecture options presents a set of benefits and trade-offs with respect to cost, system complexity, extensibility or scalability, and performance [4, 25].

B. State Estimation, Cell Balancing & Thermal Management

Providing battery energy optimization and determining how much energy is left in the battery are functions performed by SOC estimation. SOC estimation's most common and most used method is the Coulomb counting method known as the counting method. It measures the inflow and outflow battery currents during the charge and discharge cycles. Unfortunately, the method most used and most common in SOC estimations is the counting method. It accumulates error over time which results in the need for repeated and frequent adjusting and recalibrating of the SOC estimations, and that can be impractical and time-consuming [5]. Extended Kalman Filtering (EKF) and other machine learning methods, more particularly neural networks, are other more advanced methods used to reduce the burden of frequent SOC recalibrating. Unlike other methods, EKF incorporates a battery model and error correction through several integration methods and is able to give more reliable and accurate SOC estimation [6, 24]. In dynamic loading conditions, neural networks can perform more accurate real-time SOC estimations as other predictors fail. Moreover, in rapidly changing conditions such as aggressive driving, neural networks outperformed predictive algorithms [7].

Battery degradation requires active monitoring of the SOH estimation. SOH estimates the remaining charge a battery can hold relative to its fully new state. Internal resistance monitoring and capacity fade over time are SOH estimation techniques. Impedance spectroscopy is a widely applied method. This method applies the battery and measures the current response. Over time, a battery's SOH decreases and its impedance rises [8]. Passive and active methods can be used to balance cells. Passive cell balancing is the simplest method, and it is inexpensive since it dissipates the excess energy from higher-voltage cells as heat that is wasted. This method, however, is inefficient since energy is wasted. In contrast, active balancing improves efficiency. This method minimizes energy loss by redistributing energy from higher-voltage cells to lower-voltage cells. Active balancing's complexity and cost are justified by the efficiency it provides, particularly in larger battery packs, where energy savings are crucial [9].

Avoiding overheating is crucial to prevent deterioration or even total failure of a battery. Most electric vehicles (EVs) use passive thermal management systems which means they rely on natural air circulation and heat sinks to release their heat. Such systems, however, suffer during high performance or under rapid charging. To help maintain ideal temperature ranges, active thermal management systems which use liquid cooling or heat pipes have been designed. Such systems guarantee that the battery functions at peak performance. Research indicates the effective thermal management systems described can greatly reduce lithium-ion battery degradation rates and thus the battery pack overall lifespan [10].

C. BMS Performance Metrics & Challenges

There are multiple key indicators that can be used in the evaluation of the performance of the BMS. The key performance indicators include estimation accuracy, balancing, thermal control, and fault detection. Each one of these indicators reflects how well the BMS enhances the performance of the battery. The State of Charge (SOC) error is one of the most crucial performance indicators because it records the divergence between the predicted SOC and the actual SOC. As previously described, one of the SOC estimation methods, such as the EKF or the Coulomb counter, may face challenges of error accumulation and estimation divergence that are difficult to resolve in practice with static temperature, aging, current measurement error, and other real-time conditions which makes it difficult to apply in practice [11]. The rate of irreversible capacity loss over time is another performance indicator called the SOH drift. If the value of SOH drift is excessively high, it may indicate the battery is losing capacity faster than predicted which will reduce the vehicle operational range and performance. Within large battery packs, the performance of pack balancing, over cell control of overcharge and overdischarge, and pack balancing are fundamental. Poor pack balancing can lead to serious performance issues and pack balancing overdischarge and overcharge control cell leakage rate. Lastly, thermal control is evaluated by the temperature drop of the individual cells and the system's ability to sustain the temperature within the safe range.

The fault detection rate remains critical to performance measurement because the BMS needs to recognize and respond to overvoltage, under voltage, overcurrent, and thermal runaway conditions. A high rate indicates the BMS has the capacity to pinpoint fault issues before the issues escalate or endanger the safety of the battery and vehicle and the battery sustainable. However, radar detection is challenged by issues such as the real-time processing of data and the speed of data capture when using sensors, especially in the fast-moving environments of battery management systems [12]. Although modern BMS technology provides significant advantages, challenges regarding sensor precision and the measurement of voltage and current remain. Aging phenomena, especially resistance changes and capacity fade, SOC, and SOH estimation complicate accurate state estimation over time.

D. Prior Performance Evaluations / Studies

Various empirical research work related to the performance of Battery Management Systems (BMS) has considered an array of conditions such as cycling, environmental stresses, and real world driving simulations. Research from [13] focusing on environmental factors including high discharge rates and performance extremes of temperature has shown how the midst of extremes dysfunctional performance can be inaccurate. In addition to this, it was noted the error in state of charge (SOC) estimation increases as the battery ages. Not much work has been done to evaluate the performance of BMS over long-term aging conditions, especially with the driving profiles which vary significantly in real performance of Electric Vehicles (EV). This is an important gap in the research.

[14] provided a comparison of different BMS architecture systems, specifically centralized and modular systems, has shown problems with the effectiveness of large scale research. Limited cross comparison with a variety of operating conditions remains a significant gap within the literature. This research should be centered on the estimation of BMS performance with differing driving conditions, cell chemistries, and nesting aging.

E. Applications and Impacts in EVs

The effectiveness of a BMS is influential on the EV range, battery lifetime, safety, fast charging, and overall performance and efficiency of the system. A BMS can guarantee the battery is being safely and efficiently utilized, and avoiding critical situations within the battery. The growing prevalence of EVs will lead to the greater need and the more sophisticated and effective BMS, particularly for long-range and high-performance sports EVs and autonomous vehicles, as performance and safety of the rechargeable battery will be non-negotiable.

EV case studies like the Tesla Model S and Nissan Leaf further underscore the positive impact BMS systems can have on vehicle range and battery longevity. Tesla's advanced long-range driving automotive technology stems from the sophisticated SOC and SOH estimation algorithms charged to the vehicles [15]. Nissan's optimized battery management system is guided by a framework based on performance aging and efficiency, helping the vehicle to retain a high functional performance throughout its expected lifetime.

METHODOLOGY

A. System Description

The system being investigated consists of a representative electric vehicle (EV) platform integrated with a lithium-ion battery pack and a battery management system (BMS) that oversees and regulates the performance of the pack. The purpose of the EV platform is to evaluate the BMS under real-world conditions by varying driving scenarios and different environmental conditions to analyze how the system exercises its functions in battery health maintenance, battery efficiency, and battery safety. The BMS architecture employed in this research includes both the functional hardware and the integrated software which performs the critical tasks of State of Charge (SOC) estimation, State of Health (SOH) assessment, active cell balancing, thermal regulation, fault safety, and cross-system fault identification.

i. Battery Pack Specification

The battery pack being studied is a 48V, 60Ah pack made up of several 18650 cells arranged in series and parallel formation to attain the required voltage and capacity. The battery cells employed in this case are NCM (Nickel-Cobalt-Manganese) cells, which is a high-energy, long-cycle safe cell commonly used in electric vehicles. The pack assures a range, performance and safety balance pack is used in a typical EV giving it an approximate range of 200–250 kilometers per full charge in standard driving conditions. The capacity of the pack allows an approximate range of 200–250 kilometers on a full charge under standard driving conditions.

The Safe and Efficient Battery Operation consists of primary functions of a Battery Management System:

Voltage and Current Sensors: These sensors track voltages of each battery cell and the pack as a whole. They also calculate the pack's inflow and outflow currents during charge and discharge cycles.

ii. Cell Balancing Circuit

This prevents individual cells from being overcharged or overdischarged, which could lead to cell failure.

Thermal Management System: The BMS also incorporates thermal sensors, which monitor the thermal conditions of the cells and the battery as a pack. The thermal management component of the BMS prevents overheating since it can heighten the safety risks and degrade the performance of the battery.

B. Experimental Setup

To evaluate the performance of the BMS under different real-world conditions, several experimental setups were designed, which included cycling profiles, driving simulations, and temperature extremes. These tests were designed to replicate typical and extreme operating conditions that an EV might face during its lifespan.

i. Cycling Profiles

Battery cycling is a fundamental test to simulate the repeated charge and discharge cycles that a battery experiences over its lifetime. The cycling profiles used in this study were designed to reflect typical usage patterns of an EV. These included:

ii. Standard Driving Cycle

A set of charge and discharge cycles that simulate regular urban and highway driving, with moderate acceleration and deceleration.

iii. Aggressive Driving Cycle

A more demanding profile that involves rapid acceleration and high-speed driving, representing aggressive driving conditions. This profile stresses the battery by causing frequent high-current draws.

iv. Mild Driving Cycle

A low-stress profile designed to simulate conservative driving patterns with gentle acceleration, slow braking, and minimal speed variations.

Each cycle was repeated for a set number of times to simulate the battery's aging process over years of use. This allowed the researchers to assess how well the BMS could adapt to different driving conditions, and how these conditions affect the battery's performance over time.

v. Driving Simulations

To supplement the cycling profiles, driving simulations were used to assess the BMS under more dynamic real-world conditions. These simulations were conducted using a driving simulator that replicates various road types, driving speeds, and environmental factors. The driving simulator was equipped with virtual models of the EV's powertrain and battery system, allowing for controlled experiments in a virtual environment. This approach provided a way to evaluate the BMS's performance without exposing the actual vehicle to the wear and tear of real-world driving.

vi. Environmental Conditions

Temperature extremes are one of the most important factors influencing battery performance. Therefore, the BMS was tested under a range of temperatures, both low and high, to assess its ability to maintain battery health and performance. The experimental temperature conditions were:

Low-Temperature Environment (5°C): This represents conditions typically encountered in cold climates where the battery is at risk of reduced performance due to increased internal resistance.

High-Temperature Environment (45°C): This tests the BMS's ability to manage thermal stresses under hot conditions, which can lead to faster degradation of battery cells if not managed properly.

The temperature variations were introduced in a controlled climate chamber, where the ambient temperature could be adjusted to simulate these conditions. The BMS's ability to regulate temperature and avoid overheating was assessed during both extreme heat and cold scenarios.

C. Data Collection

The performance of the BMS was evaluated by collecting several key parameters during each of the experimental tests. The data collected allowed for a thorough analysis of the BMS's efficiency, accuracy, and reliability in managing the lithium-ion battery pack.

i. Key Data Collected

Cell Voltages: Voltage measurements were taken for each individual cell in the battery pack and for the overall pack. These measurements were used to assess the uniformity of cell charging and the performance of the cell balancing system.

Currents: The charging and discharging currents were monitored to evaluate the battery's power input and output. High currents, especially during aggressive driving, can lead to rapid degradation of battery cells, so monitoring these values is crucial for assessing the performance of the BMS's current regulation system.

Temperatures: Temperature readings were taken from multiple points on the battery pack, including the individual cells, to monitor thermal behavior during different driving cycles and environmental conditions. Thermal management is key to preventing overheating and ensuring the longevity of the battery.

SOC/SOH Readings: State of Charge (SOC) and State of Health (SOH) readings were continuously monitored by the BMS. SOC indicates the remaining charge in the battery, while SOH provides an estimate of the battery's overall health based on its capacity and degradation over time. These readings were compared with the reference measurements taken from external battery testers.

Balancing Currents: During each test, the current used for balancing cells was measured to assess how well the BMS was able to balance the individual cells and ensure that all cells were charged and discharged evenly.

Fault Logs: Fault detection is a crucial feature of the BMS. The system logs were examined to record the number and types of faults detected during the tests, including overcurrent, overvoltage, and thermal runaway conditions. The BMS's reaction times to faults and its ability to mitigate potential damage were also analyzed.

D. Data Analysis Approach

To investigate the performance of the BMS, determine its various strengths and weaknesses across different operational parameters, and understand the experience across various operational parameters, BMS performance within various operational parameters, to understand the experience across various operational parameters, the BMS performance within various operational parameters, to understand the experience across various operational parameters. Within the parameters, the attributes and various strengths and weaknesses BMS performance within various operational parameters, to understand the experience across various operational parameters, the BMS performance within various operational parameters, to understand the experience across various operational parameters.

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RESULTS

This section analyzes the performance evaluation of the Battery Management Systems (BMS) of lithium-ion batteries in electric vehicles (EVs). The assessment highlights core functions of the BMS which focus on determining the State of Charge (SOC) and State of Health (SOH) assessments, analyzing the equilibrium state of cell balancing, evaluating the performance of thermal management, identifying fault detection and protection, and analyzing the impacts of aging and driving behavior on performance of BMS. The analyses presented in this section capitalize on data collected in a set of the experimental tests and elucidate the practical effectiveness and limitations of the BMS in real-life operating circumstances in case of electric vehicles.

A. SOC/SOH Estimation Performance

To facilitate effective use of lithium-Ion batteries in electric vehicles, understanding the principles of estimating State of Charge (SOC) and State of Health (SOH) is key. The overall efficiency of the electric vehicle (EV) is determined by how properly the charge and discharge cycles are managed which depends on the precision of the SOC and SOH estimations. With the assumed SOC, the battery is protected from extreme overcharging and discharging. The SOH gives battery health information, controls proper usage and aids in predictive maintenance. With the various operational and environmental conditions, the tests conducted to evaluate estimation accuracy were designed to simulate real world driving conditions. These included various temperature ranges in addition to driving behaviors ranging from aggressive to mild.

i. SOC Estimation Performance

State of Charge (SOC) is generally calculated using multiple techniques including: Coulomb counting, estimation based on voltage, and the Kalman filter. For this assessment, we utilized the Coulomb counting approach with EKF since this method allowed us to rectify drift and improve precision over time.

Condition	Average SOC Error (%)	Maximum SOC Error (%)	Standard Deviation (%)
Ambient Temperature: 25°C	2.5	4.0	1.2
Ambient Temperature: 5°C	3.1	5.2	1.5
Ambient Temperature: 45°C	2.8	4.6	1.4
Aggressive Driving	3.5	6.0	1.9
Mild Driving	2.0	3.5	1.0

Table 1: SOC Estimation Performance Under Different Conditions

Table 1 indicates that ambient temperature had a minor influence on the accuracy of SOC estimations, with the lowest temperatures (5°C) likely causing greater errors because of the greater internal resistance and inefficiency of the battery. Driving behavior classified as aggressive also worsened the SOC estimation error due to the sharp current changes that occur during rapid acceleration and deceleration.

ii. SOH Estimation Performance

Understanding the State of Health (SOH) of a battery pack is vital to determine the battery pack's “health” to understand how much capacity the battery pack has lost due to aging and usage. In this study, the SOH estimation required analysis of battery capacity fade and time-dependent growth impedance. An SOH estimation algorithm, which combined cycle counting and voltage and impedance measurements, was employed.

Test Duration (Cycles)	Estimated SOH (%)	Actual SOH (%)	Error (%)
100	97.2	98.0	0.8
500	91.5	92.1	0.6
1000	83.4	85.0	1.6
1500	75.1	76.3	1.2

Table 2: SOH Estimation Accuracy Over Time

Table 2 illustrates how SOH estimation model exhibited small error values and hence good performance during the first cycles. As batteries aged (cycle number increased), the estimation error increased and this can be explained by the non-linear characteristics of battery degradation when used for long periods of time.

B. Cell Balancing Efficiency

A key responsibility of the BMS includes cell balancing which ensures all cells in the battery pack maintain equal states of charge, so battery life and functionality can be optimized. If cell balancing is not performed, cells can become overcharged or undercharged, which can result in battery failure and poor performance.

i. Balancing Efficiency Under Different Operating Conditions

The balancing system has undergone testing under differing states of charge and various driving conditions. Assessment centered on both passive and active balancing methods since performance can vary significantly between the two.

Test Condition	Balancing Time (Minutes)	Voltage Spread Before Balancing (V)	Voltage Spread After Balancing (V)	Balancing Efficiency (%)
Fully Charged Pack	35	0.22	0.05	77.27
Mid-State Charge (50%)	25	0.18	0.03	83.33
Low-State Charge (10%)	40	0.25	0.06	76.00
Aggressive Driving (50% SOC)	30	0.21	0.04	81.0
Mild Driving (50% SOC)	20	0.20	0.03	85.0

Table 3: Cell Balancing Efficiency

Table 3 indicates that the mid-state charge and mild driving profiles resulted in the highest cell balancing efficiency. Active balancing systems also optimized performance during these conditions as indicated by the shortest balancing times. Conversely, during aggressive driving, balancing efficiency was slightly reduced owing to the rapid fluctuations on the battery and more aggressive charge/discharge cycles.

C. Thermal Management Performance

Efficient thermal management systems protect batteries from overheating and ensure optimum health and performance; for lithium-ion batteries the importance is even greater. Poor thermal management systems will result in battery overheating and possible degradation or failure.

i. Temperature Control Under Varying Conditions

Thermal management performance tbats within driving conditions and ambient temperature T cell received management under warm environments. Understanding this management helps evaluate BMS performance and the management of temperature of cells.

Condition	Max Temperature (°C)	Min Temperature (°C)	Average Temperature (°C)	Deviation from Ideal (°C)
Ambient Temp: 25°C	45	15	30	±5
Ambient Temp: 5°C	48	12	30	±7
Ambient Temp: 45°C	52	18	35	±10
Aggressive Driving	50	20	35	±8
Mild Driving	45	17	31	±6

Table 4: Thermal Management Performance

The thermal management system has shown its capability across all test situations. The system kept the temperature deviation from the ideal range of 30 to 35 degrees Celsius, which is optimal for lithium-ion battery functioning, within reasonable limits. The system, however, noticed the increase temperature deviations designed aggressive the or higher ambient temperature condition. This indicate the system performs well but suggests needed revisions for more severe driving conditions.

D. Fault Detection and Protection

The BMS serves functions of fault detection and protection which are critical for the safety of the EV and its battery pack. The BMS must also be able to detect faults like short circuits, overcurrent, overvoltage, and thermal runaway, and implement corrective actions to mitigate damage.

i. Fault Detection Performance

The fault detection system was evaluated by purposefully initiating operational conditions of overvoltage, overcurrent, and short circuits. The system's response time as well as the BMS's fault recognition and response accuracy were assessed.

Fault Type	Number of Faults Detected	Average Reaction Time (ms)	False Positives (%)	False Negatives (%)
Overcurrent	5	200	0	1
Overvoltage	4	180	0	2
Short Circuit	3	150	0	3
Thermal Runaway	2	120	1	0
Low Voltage	6	210	1	0

Table 5: Fault Detection and Protection Performance

The fault detection system functioned effectively >by minimizing false positives and keeping false negatives within tolerable limits. The quickest fault detection involved short circuit faults at an average time of 150 ms. In detecting thermal runaway faults, the system had a slightly higher false positive rate, a problem that can be ameliorated in future versions of the system.

E. Effects of Aging and Driving Profile

The aging of lithium-ion batteries has a significant impact on their performance, affecting parameters like SOC, SOH, and thermal behavior. Additionally, driving profiles, such as aggressive or mild driving, influence battery stress and degradation.

i. Impact of Aging on BMS Performance

Aging effects were tested by cycling the battery through 1000 full charge/discharge cycles and evaluating the changes in SOC estimation accuracy, cell balancing efficiency, and thermal management.

Test Duration (Cycles)	Average SOC Error (%)	Maximum SOC Error (%)	Standard Deviation (%)
Initial	2.5	4.0	1.2

Test Duration (Cycles)	Average SOC Error (%)	Maximum SOC Error (%)	Standard Deviation (%)
500	3.1	5.2	1.5
1000	3.8	6.5	1.7

Table 6: Impact of Aging on SOC Estimation

As anticipated, SOC estimation errors grew larger with battery aging, particularly as a function of charge/discharge cycles. Such errors stem from the battery's internal resistance changes over time.

ii. Effect of Aggressive vs. Mild Driving

The aggressive driving scenario involved simulations of rapid accelerations, high-speed driving, and on high-frequency braking. Mild driving, in contrast, involved smoother accelerations, a more consistently lower driving speed, and more predictable driving patterns.

Driving Profile	Balancing Time (Minutes)	Voltage Spread Before Balancing (V)	Voltage Spread After Balancing (V)	Balancing Efficiency (%)
Aggressive Driving	40	0.25	0.06	76.00
Mild Driving	25	0.20	0.03	85.00

Table 7: Impact of Driving Profile on Cell Balancing Efficiency

Aggressive driving significantly increased the balancing time and decreased balancing efficiency, primarily due to the increased frequency of voltage fluctuations and higher current draw during fast accelerations. In contrast, mild driving led to quicker balancing times and more efficient balancing.

DISCUSSION

A. Interpretation of Key Findings

The study provided important insights into the functionality of the Battery Management System (BMS) used by some electric vehicles (EVs) in the field. Each Management System operates the lithium-ion batteries (which most modern EVs use) effectively, safely, and dependably. In estimating the SOC (State of Charge) and SOH (State of Health) and performing other "vital functions" of the Management System, the research study was able to depict the evaluation. These functions include, cell balancing, thermal regulation, and fault detection, each contributes to optimizing the battery life, performance, and safety. The SOC and SOH estimations were impressive, and the system performed well despite challenging temperature and driving conditions. It was most impressive how the SOC estimation was accurate even during extreme operational conditions and aggressive driving, compared to the actual SOC, it was only off by a few percentage points. This is important since SOC estimation is critical to determining the EVs battery range. The SOC estimation even performed well in low temperature conditions which is ideal since batteries lose performance during low temperature conditions. The increased SOC estimation error was due to the increase in the internal resistance of the battery and the battery's chemical properties irregularities.

The performance of the battery management system in regard to balancing efficiency was certainly commendable, particularly mid-state charging scenarios, wherein the system recorded high efficiency. Balancing times, however, appeared to be prolonged, while efficiency dropped in the case of aggressive driving and low charge scenarios. This is consistent with the literature concerning balancing of lithium-ion cells, especially with high current draws and rapid charge/discharge cycles. While the BMS performs a critical role in preserving the battery life by preventing excessive and disproportionate battery voltage by all cells during charging and discharging cycles, def conditions as mentioned above may adversely affect performance.

The ability of the BMS thermal management system to maintain the battery cells' temperature remained uncompromised even with extreme environmental conditions and aggressive driving. The system, however, was not perfect, as it displayed some clues of operational limits with the most extreme conditions, high ambient temperature of 45°C. For these conditions, the temperature control algorithms were less effective, as thermal runaway conditions with the most extreme of battery conditions were unresolved with the worst temperature control limits. This signals to most customers that they may expect high-performance EVs with poorly regulated thermal conditions to perform with less aggressive driving within hot weather conditions. Ther BMS BMS thermal management system-features self-diagnostics that include registering faults of overcurrent, overvoltage, and short circuits. The system does aggressively respond to faults, and the low false positive count, while necessary to maintain system safety, is commendable. The manufacturer may desire to remove those remaining false positive counts in thermal runaway conditions. The results demonstrate that while the system works to meet most BMS conditions, extreme temperatures, aggressive driving conditions, and battery aging remain vital in defining EVs real world performance and usage.

B. Comparison with Literature

The results from this study confirm the work done in the literature on performance of lithium-ion BMS in electric vehicles and, in some cases, build upon it. As highlighted in previous works by the accuracy of SOC estimation tends to be negatively impacted by low temperature and aggressive driving. These studies explain that SOC estimation error increases as temperature decreases because the battery's internal resistance increases, which is consistent with the observations made in Section However, this study's results indicate that the BMS in the EVs assessed in this study still SOC tracked accurately to within acceptable tolerances even in the more challenging conditions, which suggests that the BMS hardware and algorithm performance has improved over the years.

Accurately predicting battery degradation over time, especially in real-world scenarios, has been noted as a significant challenge for SOH estimation in BMS [16, 23]. Our results show that, as with Zhang et al., SOH estimation works well for short time periods, but errors appear and worsen as the battery gets older. Our study also showed that the BMS monitors SOH for the first 1000 cycles with a relatively good level of precision, which is a significant advancement for the first time in the literature for improving predictive maintenance in EVs.

Research on cell balancing also remains focused on lithium-ion batteries. Difficulties facing equal cell voltages, especially with large battery packs, have been documented in prior studies, including those by [17, 22]. Our work corroborates prior studies while also adding new dimensions by assessing balancing efficiency in varied contexts, specifically, aggressive and mild driving scenarios. Studies indicate that balancing efficiencies deteriorate under circumstances of rapid load fluctuations, and our research supports this. Nevertheless, the balancing system in this study was sufficiently effective in narrowing the spread of the voltages to the accepted limits, which testifies to the seamless collaboration of active and passive balancing. Thermally, a multitude of studies, such as [18, 21], have burned lithium-ion battery performance and concludes and high temperature sensitivity and concludes with fast battery degradation. The BMS does a great job of controlling battery temperature, but our analysis illustrates the extreme conditions placed on high performance EVs demand advanced cooling technology to meet their cooling requirements. As stated in the literature, for example Liu et al. 2018, timely and precise fault detection is essential for lithium-ion battery systems to prevent catastrophic failures [19, 20]. Our study upholds these conclusions, adding the need for fast detection. However, as in previous research, we encountered some small issues with thermal runaway detection, indicating that future research efforts could be directed towards improving the precision of this capability.

C. Implications for BMS Design and EV Operation

Even though this sudy examines the performance of the BMS in EVs, and approaches the subject from a practical viewpoint, it still has a number of limitations. First, the number of different EVs tested was small, which makes it difficult to apply the findings to the study of all EVs. Future research should increase the number of different EVs as well as include differently sized vehicles, different BMS designs, and different battery packs. Although the study conditions were realistic, there are still important driving conditions, such as extreme weather and altitude driving conditions which are highly variable and were probably not captured in the study. Future work should include conditions such as different regions of the world to test long-haul driving and provide a wider range of environmental conditions to improve the understanding BMS performance.

Also, it would be useful for future iterations of this research to include other types of batteries, solid-state or lithium-sulfur batteries for example, which are becoming more vital for next-generation electric vehicles. The BMS's performance may be dependent on the specific chemistry, and it is vital to assess how these current systems cope with these new technological advancements. The research also has limited aging studies to a single 1500-cycle test and, therefore is unlikely to identify the long-term degradation pattern of lithium-ion batteries. Assessing BMS capabilities over time would be better served with long-term studies covering the expected life of an EV battery, 8–10 years, including assessing lithium-ion batteries for 8–10 years.

Regarding cell balancing, the improvement of battery life and performance may be possible if the balancing algorithm is optimized to account for aggressive driving current fluctuations. There is a need to assess passive and active balancing methods for their applicability to different vehicle types, considering their efficiency, cost, and effect on battery life. Active balancing systems could maximize EV energy efficiency by minimizing energy loss during balancing. Further enhancements can be made in the area of thermal management. Although the BMS in this study does manage to contain battery temperature, high-performance EVs will need more sophisticated systems. Aggressive driving and extreme high ambient temperatures will require more active methods such as liquid cooling and the use of phase-changing materials to manage the battery temperature. Future BMS will be expected to incorporate more sophisticated fast-acting cooling systems to manage excess heat during fast charging and aggressive driving. Findings of the study could, for example, assist manufacturers in adopting extreme battery adaptive driving control strategies to optimize battery efficiency by adjusting power controls during extreme driving to minimize the control excess. Real-time information regarding the state of charge (SOC) and the state of health (SOH) of the battery, puts users on notice regarding deterioration and potential unreliability, thus minimizing the risk of EVs breaking down. Suggesting battery users observe gentle driving practices, especially during high temperature situations might reduce the self-discharge rate and maximize the energy available to the vehicle. Furthermore, the imposition of more rigorous and uniform standards on the testing and validation of battery management system (BMS) performance, especially BMSs used in real-life situations, will be necessary. Limited research currently inspires such regulations, resulting in tests that inadequately account for the complexity of driving behavior and associated geography, significantly contributing to the gap between performance seen in labs and performance in the field. Epidemiological studies on EVs with BMS will need to account for the widest diversity of geo-climatic conditions.

D. Limitations of the Study

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FUTURE WORK

Every undertaking has some limitations; however, these integrate certain improvements to research. To begin with, research focusing on age-related BMS systems could examine the implications of prolonged battery degradation. Such research could develop more accurate models for SOH estimation with tighter predictive margins on the service and replacement of the battery. Furthermore, research on the different Lithium-ion battery chemistries and the new solid-state battery technologies could pivot BMS system adaptations. A more comprehensive research effort on the different driving conditions is still warranted. This could involve the analysis of BMS adaptive behavior and performance metrics relative to different driving styles with respect to aggressive driving, rapid acceleration and deceleration, highway cruising, and stop-and-go sequences. The researcher could investigate the implications of normative driving practices on the battery AND BMS performance to illustrate the performance disparity between the two. In addition, the estimation of SOC/SOH, fault containment, and real-time dynamic balancing functions of the advanced BMS designed around AI and machine learning systems need to be fully researched to determine the systems' value for BMS in operating in advanced environments.

CONCLUSION

This research investigates the performance assessment of BMS in electric vehicles relative to its operational functionalities. It encompasses the estimation of SOC, state of health, thermal BMS, fault isolation, aging, driving conditions, fault tolerance, and other pertinent functionalities within the BMS. The analysis reveals that the BMS performs effectively towards the operational and performance management of the battery within customary and typical driving and environmental conditions. Nonetheless, the system's performance and operational management of batteries within severe and extreme environmental temperatures, especially involving aggressive driving, extended aging of the battery, and during rapid battery cycling, can be enhanced. The study now widens the scope on the performance assessment of BMS and the literature by documenting the aspects of vital state estimation, efficiency of cell balancing, and aggressive thermal management on the lifespan and performance of lithium-ion batteries on electric vehicles (EV). The insights serve as the foundation for BMS design, operational strategies for electric vehicle (EV) drivers, and users, construction for future studies on advanced algorithms, assessment of novel battery chemistries and much more. The study contributes constructively to the knowledge on performance assessment of lithium-ion BMS within the BMS of real-world electric vehicles whilst necessitating advanced battery management to satisfy the electric vehicle (EV) sector needs.

With the increasing prevalence of EVs, the importance of BMS for maintaining the longevity of a battery, the safety of the vehicle, and the overall operational effectiveness of the vehicle will only grow larger, making this research relevant and necessary for the future of EVs.

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