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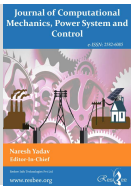

An Extensive Review of Recent Development of Battery Management Systems

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Abstract: Long lifespans, excellent power production, and enhanced safety are the advantages of the efficient Battery Management Systems (BMS). It retrieves the pack of current and voltage for every cell regularly to give these functionalities. Numerous industries utilize BMS to track, regulate, and improve battery security and performance. Similarly, it can also improve the battery life and ensure the use of effective energy. Moreover, there are various BMS types, including centralized or distributed designs and active or passive systems are employed in the different technologies depending on the application. However, it has drawbacks such as poor adaptability to operating conditions, inefficiency in detecting hidden internal battery failures, insufficient data processing and storage, inaccurate state estimations, as well as high cost and complexity of sophisticated wired or emerging wireless systems. These limitations hinder the real-time adaptability of BMS, especially under dynamic environmental conditions or high-demand applications such as electric vehicles and aerospace systems. To overcome these obstacles, AI-driven approaches, Internet of Things-based systems, and some other approaches are used in the surveys, which have become more and more popular in recent years. To give an in-depth overview of the current research, we performed a literature review that concentrated on the most significant papers that were published in Google Scholar, Springer, Science Direct, and IEEE journals between 2020 and 2025. Voltage, current, convergence time, battery State of Charge (SOC) estimation, State of Health (SOH) evaluation, and system efficiency were all taken into consideration when analyzing these investigations. Comparative analysis of these parameters provides valuable insights into the effectiveness of different BMS architectures and their computational methods. In order to promote future advancements in BMS, current developing equipment can be integrated with digital twins, Artificial Intelligence (AI), and the Internet of Things (IoT) to enable predictive maintenance and more reliable solutions.

Keywords: State of Charge; Artificial Intelligence; State of Health; Internet of Things; Battery Management System

Nomenclature

Abbreviation	Description
SOC	State of Charge
BPNN	Back Propagation Neural Network
ICE	Internal Combustion Engine
ESS	Energy Storage System
AI	Artificial Intelligence
EV	Electric Vehicles
ICE	Internal Combustion Engine
IB-DRN	Incipient Bat-Optimized Deep Residual Network
OCV	Open Circuit Voltage
CO	Carbon Monoxide
NO	Nitrogen Oxides
CO2	Carbon Dioxide
SO2	Sulfur Dioxide
SOH	State of Health
EMF	Electro Motive Force
LSTM	Long Short-Term Memory
EAI	Explainable Artificial Intelligence
DL	Deep Learning
MAE	Mean Absolute Error
RF	Random Forest
LSTM	Long Short-Term Memory
RBNN	Radial Basis Neural Network
LSTM	Long Short-Term Memory
MSE	Mean Square Error

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RMSE	Root Mean Square Error
ML	Machine Learning
EMPA	Enhanced Marine Predators' Algorithm
BMS	Battery Management System
IWHODL-BMS	Improved Wild Horse Optimizer with Deep Learning Enabled Battery Management System
ABiGRU	Attention-Based Bidirectional Long Short-Term Memory
HEV	Hybrid Electric Vehicle
IoT	Internet of Things
CNN-GRU-LSTM	CNN and Gated Recurrent Unit-Long Short-Term Memory
LFP	Lithium Iron Phosphate
LFP	Lithium-Ion Ferrous Phosphate
SPM	Single Particle Model
NTGK	Newman, Tiedemann, Gu, and Kim
MOR	Model Order Reduction
EIS	Electrochemical Impedance Spectroscopy
DOD	Depths Of Discharge
SEPIC	Single-Ended Primary-Inductance Converter
AFE	Analogue Front End
CHAIN	Cyber Hierarchy and Interactional Network
DT	Digital Twin
AI	Artificial Intelligence
EKF	Extended Kalman Filter
XGBoost	Extreme Gradient Boost
BTMS	Battery Thermal Management System
UAVs	Unmanned Aerial Vehicles
DNN	Deep Neural Networks
SPCA	Sparse Principal Component Analysis
ML	Machine Learning
RCP	Rapid Control Prototyping
HIL	Hardware-In-The-Loop
ECMs	Equivalent Circuit Models
RNNs	Recurrent Neural Networks

1. Introduction

Since the beginning of the 21st century, the world has been consumed by the digital economy, digital transformation, which are growing [1], and conflict in the battery manufacturing industry has become ferocious [2]. The increasing global dependence on electrification and smart technologies has further intensified competition in the energy sector. The focus of energy storage strategies has evolved with technological advancements and revolutions within the traditional battery sector. Similarly, EVs, renewable energy storage, micro/smart-grid applications, and other fields have all experienced the use of ESS [3]. However, ICEs can be reliably replaced by modern EV generations. Fossil fuel is used by ICE-based trucks, ships, load, and aircraft, respectively. This transition is driven by the need to reduce emissions and enhance energy efficiency in transportation and industrial applications. The two main sources and the contributors for the emissions of CO2, SO2, CO, and NO are industry and ICE [4]. The greenhouse effect is caused by air pollution from these gases.

The SOC should be valued by the BMS under various circumstances. Battery capacity, charge, and discharge states will all be optimized as a result [5]. Accurate SOC estimation ensures the longevity and reliability of battery systems, preventing overcharging and deep discharging conditions. A variety of techniques are available for determining SOC. Current count method, Impedance measurement-based estimation methods [7], Kalman filter and observer technique estimation [6], EMF, OCV, least squares estimation, and their mathematical calculation formulas have been provided in the BMS-based model. To ensure the optimal performance of the battery pack, a typical BMS configuration includes many functions, such as data collection and analysis, fault diagnosis and safety alarm, battery state estimation and prediction, cell balancing and monitoring, intervention strategies, thermal management, and data communication are employed in the process [8]. These functionalities collectively enable BMS to maintain safe operating limits, enhance efficiency, and extend the service life of energy storage systems.

Although universities and businesses have been studying BMS extensively for decades, there are still a lot of technical issues that need to be resolved, which will make BMS development extremely difficult [9]. Challenges include managing large-scale data, ensuring cybersecurity in connected systems, and developing low-cost yet highly reliable architectures. For instance, some crucial battery parameters that were evaluated in the laboratory are less reliable compared to the larger scale from cell, module, and battery pack to the battery system of an EV [10]. This electrical system architecture has problems with

transmission inefficiency, security, and dependability, all of which become more significant as the percentage of intermittent renewable energy sources rises [11]. Consequently, there is a growing need for intelligent, self-adaptive BMS architectures capable of responding dynamically to fluctuating power demands and environmental conditions. The advantages of having ESS are intelligently controlled; however, it is becoming more apparent as connected devices and AI develop. Thus, the grid-scale energy storage systems are one of the solutions to balance these supply and demand challenges [12].

BMSs typically employ a modular design and have various hierarchical levels for their functionalities [13]. To ensure battery safety, BMS dependability is crucial, both in terms of construction and noise immunity [14]. This is particularly applicable for situations that need a high level of safety, such as those in the automobile and space sectors [15]. Therefore, robustness, fault tolerance, and high-speed data processing are essential design considerations for future BMS implementations. These factors make it necessary to thoroughly examine the BMS's software and hardware capabilities [16]. A number of benefits, including high power and energy density, extended life cycles, high voltage, and low self-discharge rates, make BMS-based technology viable for EV applications at this point [17]. However, batteries' temperature and aging propensity limit their precision and efficiency in energy storage [18,19]. Numerous IEEE and Google Scholar articles on BMS examine their vital function in battery monitoring and control, particularly in smart grids and EVs [20]. The estimation of SOC and SOH, cell balancing technologies, as well as the integration of wireless and IoT-based systems, are used for improving the safety and monitoring of intelligent controllers by utilizing methods like fuzzy logic, which are some of the significant subjects covered in this work. They also describe the strengths and limitations of the existing BMS-based technologies in putting such systems into practice, as well as the hardware components. This study contributes by consolidating these developments, identifying existing gaps, and proposing possible enhancements through adaptive and data-driven approaches. This paper observes and assesses current studies on battery management systems for various technologies with compensating strategies. It further discusses methodologies, achievements, and future scopes of the model by examining the current battery management system models' power performance, SOC, SOH, and efficiency.

The structure of the survey is given as follows: Section 1 provides an overview of the battery management system. Research based on state-of-the-art is reviewed in Section 2. In a similar vein, Section 3 provided an in-depth evaluation of a number of techniques employed in the current work. The study and discussion of the several technologies utilized by the BMS are presented in Section 4. Research gaps are presented in Section 5, while the conclusion and future scope of the work are highlighted in Section 6.

2. Research Based on the State of the Art

BMSs have been developed in different system models for a variety of practices. These practices include monitoring voltage, current, and temperature; estimating SOC and SOH; and offering protection against overcharging, overheating, and overcurrent to extend battery life and ensure safety. In recent years, these functions have evolved from simple analog systems to intelligent, data-driven frameworks capable of adaptive decision-making. Such advancements are primarily due to improvements in sensor technologies, embedded systems, and real-time data analytics, allowing BMSs to process high-frequency signals with greater precision. The main functional areas of a BMS survey are cell balancing, thermal management, communication, safety management (avoidance of overcharging and overheating), as well as performance and state estimation. The hardware and software architecture of the system, different battery models, testing protocols, similarly, the benefits and limitations of selected survey's BMS-based technology are other subjects discussed in this work. Hardware design primarily focuses on signal acquisition, protection circuitry, and modular connectivity, while software aspects involve algorithms for estimation, fault detection, and control. The BMS for EV-based models is also covered in these surveys to explain its vital function in EV battery performance monitoring and control, safety assurance, and battery longevity. These surviving publications provide reviews of the BMS-based electric vehicles, implementation of BMS for different frameworks, BMS collaboration, analysis, and assessment. It demonstrates their vital roles for many battery kinds and uses, including robots and EVs.

3. Survey of Different Topics for Battery Management Systems

This section provides a thorough analysis and summary of the various approaches and strategies that experts and researchers have employed BMS for various machinery operations so as to monitor, regulate, and protect batteries for the best and most secure machinery functioning. Recent research emphasizes integrating intelligent algorithms and connected infrastructures to enhance battery safety, extend lifetime, and improve operational reliability across different applications. These strategies include advanced control

methods for performance optimization, state estimate algorithms for accurate SOC and SOH assessment, fault detection, machine learning for maintenance planning, and adaptive charging.

3.1 IoT-Based Battery Management Systems

In 2021, Le *et al.* [1] proposed an IoT Network Management within the Electric Vehicle Battery Management System. The model examined IEEE Std 802.15.4 Time Slotted Channel Hopping wireless networking, which is a standardized procedure for low-power and lossy systems. This standard enables reliable data transmission in energy-constrained environments, making it ideal for vehicle-scale wireless monitoring. Initially, the model described their real-world tests to evaluate the linkage quality for wireless nodes placed at the Medium Access Control layer inside an EV battery pack. Based on the outcomes of the studies, they then proposed two topology management and scheduling strategies utilizing methods called Simple Descent and Linear Programming. These strategies helped optimize communication performance by minimizing packet loss and latency within the battery pack's sensor network. Their objective was to transport data efficiently while adhering to battery management constraints.

In 2022, Kumar *et al.* [2] created an Internet of Things BMS based on LR parameter estimation and an ORMeshNet gateway topology. The proposed system combined advanced estimation algorithms with robust IoT communication protocols to achieve real-time performance monitoring. Methods for accurately and consistently estimating SOC and SOH were initially created based on an LR before any other mechanisms, including the BMS, were tracked or diagnosed. This approach outperforms existing estimating techniques in terms of both convergence rate and fault tolerance. Moreover, the framework's design highlights the importance of coupling accurate modeling with efficient communication for achieving dependable monitoring across distributed nodes. In order to satisfy the operational limits of battery current, voltage, and state of charge, the SOP estimator uses the updated parameters and estimated states to produce more accurate peak power estimates. The estimated results were then transferred using an IoT platform that included OTH-AJS for node selection and LND-BES for optimal routing based MeshNet gateway protocol for data transfer for monitoring. The proposed method produced an 83.98% Goodput, an 87.98% PDR, and an 88.97% throughput. In comparison to current approaches, experimental results demonstrated a significant improvement in parameter estimation with greater throughput, PDR, and effective value.

In 2021, Yang et al. [5] proposed a general structure for a cloud-based BMS that uses an end-edge-cloud architecture, explaining the structure and purpose of each link. This architecture enables distributed computation and hierarchical data processing, offering an efficient framework for real-time analytics. The functionality of conventional BMS systems, such as fault detection, cell balancing, temperature management, and state-of-X estimation, could be accomplished using more sophisticated and efficient algorithms. Multi-scale insights are provided by the CHAIN framework. The battery smart monitoring and management platform could make it possible to build control strategies, save operational data to provide an extensive overview of the microscopic evolutionary law, and display battery performance numerically. The remote updating capabilities of the controller and the multi-scale integrated models' methodologies were currently more crucial for the cloud-based BMS's accurate management and online system upgrade. This continuous improvement mechanism supports adaptive firmware updates and long-term system learning, aligning with Industry 4.0 paradigms. The usefulness of this approach was shown for both automotive applications and any battery energy storage system, and it provided a thorough framework for intelligent and connected battery management in the future.

In 2024, Krishna et al. [16] proposed and implemented into use a customized hardware solution based on LoRa and IoT, equipped with a gateway to fold and log certain metrics, including temperature, cycle, terminal voltage, current, charge voltage, and SoC and SoH, into a cloud system. The choice of LoRa technology provides an extended communication range with minimal power consumption, which is particularly beneficial for large-scale energy storage applications. A FLoRa simulation based on OMnet++ was developed in order to analyze the power consumption and residual energy of the customized LoRa nodes. The parameters chosen for the simulation included a bandwidth of 125 kHz, a transmission power of 2 dBm, a spread factor of 7, and a carrier frequency of 433 MHz. The simulation results showed that Node 3 had the highest mean power consumption (0.028233) and total energy consumption (0.146592), while Node 0 exhibited the lowest mean power consumption (0.023413) and total energy consumption (0.070204). These findings illustrate the trade-offs between energy efficiency and communication reliability across different LoRa configurations. Also, a thorough dataset that included current, voltage, and time was developed and used to precisely measure the battery's health and capacity, which may be useful for forecasting in the future.

3.2. Cell Balancing Techniques

In 2021, Duraisamy et al. [7] implemented a ML- based balancing control algorithm to select the best balancing resistor based on temperature rise, C-rate, balancing time, and degree of cell imbalance so as to enhance balancing time and manage power loss as efficiently as feasible. This approach represented an important step toward integrating intelligent control into conventional passive balancing methods, enabling adaptive adjustments based on real-time cell data. To get the best thermal characterization and minimize power loss, the passive balancing system uses variable resistors. RBNN, LSTM, and BPNN are used to assess the proposed system's performance. Each neural model provided unique advantages, with LSTM performing best in handling sequential voltage data and predicting balancing dynamics. The performance of the balancing model was evaluated by comparing the proposed approaches using performance indices such as MAE, RMSE, and MSE. Error analysis of the balancing system was performed to optimize balancing parameters. Using ML algorithms, the MATLAB-SimScape environment was used to test the potential optimization scope for adopting passive balancing.

In 2023, Kumar et al. [17] proposed a switched-resistor passive balancing-based method for balancing cells in a BMS. The researchers emphasized the trade-off between cost-effectiveness and thermal efficiency, a persistent challenge in passive balancing frameworks. In an electrical circuit, resistors were used to eliminate extra voltage and balance the voltage that was accessible at the battery cell terminals. The results of cell balancing showed that the electrical circuit was capable of sustaining a steady voltage across every cell. The process of balancing involved changing the charge level of each cell. By removing excess charge from cells, passive balancing releases energy as heat. Although a passive cell balancer was an inexpensive and simple solution, it required a long balancing procedure and had a low energy efficiency for cell balancing because of thermal loss from a resistor. For portable applications like EV and low-power electronics, this passive cell balancer offered a dependable and efficient technique. The bisection method was used to estimate the power limits while charging and discharging.

In 2023, Manas et al. [14] offered an architecture that combines a simulation and a hardware demonstration of the continuous on-time control method for analytical temperature, voltage, and current measurement in EVs. The optimum power supply for the proposed congregated BMS process was provided by an AFE, balancing circuits, and a SEPICDC-DC converter. Temperature, current, and voltmeter measurements from meters and sensors verify the efficacy of the proposed system design performance. The proposed BMS and conventional measurements had comparatively small numerical errors for temperature (0.09 ◦C), voltage (0.09 V), and current (0.05 A). Such precision demonstrates the readiness of this system for commercial EV deployment, especially where thermal stability and reliability are critical. The proposed clustered BMS architecture might eventually control temperature, prevent excessive charging and draining, and maintain equilibrium among the battery cells inside a particular battery module, according to benchmarked simulation and hardware results.

3.3 ML/DL Algorithms

In 2022, Shahriar et al. [3] presented a CNN-GRU-LSTM approach, which uses an EAI model based on RNNs to estimate the SOC of batteries. This model leveraged the combined strengths of convolutional and recurrent layers to capture both spatial and temporal patterns in battery data. The SOC was explicitly coordinated with the cell characteristics. The complex connection between the battery SOC and the temperature, voltage, and current monitoring signals was developed using the DL approach. Initially, all temperature data were used in the training process so that the trained model could compute the SOC at various ambient temperatures. The proposed method was able to capture the relationships on time inside the network weights, which resulted in more reliable, accurate, and stable predictions of the SOC when compared to some other existing networks. The hybrid model's MAE varied between 0.41% and 1.13% when it functioned at temperatures between -10 ^{O}C and 25 ^{O}C. In order to identify the primary features that drive the estimation process, the decision-making process of the battery SOC model was also described using the EAI. Such interpretability enhances user trust and supports the integration of explainable AI into energy management frameworks.

In 2025, Naresh et al. [4] offered an evaluation of the efficacy of fake fault induction methods, such as overcharging and overheating, in validating diagnostic algorithms. The inclusion of controlled fault induction provides a valuable benchmark for training more resilient AI systems capable of recognizing early fault symptoms. The use of ML in BMSs was also examined; the Expert Knowledge Integration network and Feature Fusion proved to be successful in this regard, exceeding traditional techniques in terms of speed and accuracy while attaining an anomaly detection rate of 98.5%. For its accuracy and scalability in handling sub-extreme fault scenarios, the hybrid diagnostic frameworks that integrate machine-learning and model-based techniques are preferred. This study highlights the value of collaborative research in improving fault detection in the future, with a focus on adaptive ML algorithms and practical challenges to guarantee the long-term sustainability of modern battery models.

In 2023, Kosuru et al. [8] proposed a system for battery data, particularly lithium-ion batteries, that enables the classification and identification of defective battery sensors and transmission data using DL. By focusing on data integrity and fault isolation, this study contributed to the development of secure BMS architectures suitable for high-risk domains. The sensor data was initially gathered by the model, and z-score normalization was used for preprocessing. SPCA was utilized to extract the features, and EMPA was employed for selecting the features. The BMS may be more secure and reliable compared with the proposed IB-DRN-based false battery data recognition and categorization system. The effectiveness of the proposed technique was demonstrated and evaluated by experimental research, MATLAB (2021a) simulations, statistics, ML, and a DL toolkit. It has been demonstrated to be better than conventional methods.

In 2022, Vasanthkumar et al. [10] presented an IWHODL-BMS for IoT-based HEVs. This hybrid architecture represents a convergence between optimization algorithms and deep learning, showing promise for large-scale deployment in connected mobility systems. The ABiGRU method was used by the given IWHODL-BMS to accurately determine the SOC in HEVs. As a hyperparameter optimizer, the IWHO method was used to improve the ABiGRU technique's SOC estimate performance. The input was represented more simply and accurately when the ABiGRU model was used. A comprehensive simulation result showed that the IWHODL-BMS model outperformed the other methods on a number of measures.

In 2023, Nagarale et al. [20] presented an experimental investigation for the data-driven prediction of lithium battery parameters such as SOC and SOH using AI and DL algorithms like BiLSTM and LSTM. This experimental approach offered a solid comparative framework for evaluating gradient descent variants in deep sequential models. The approach used a variety of gradient descent optimization techniques with other default parameters that had constant and adjustable learning rates. The precision of the MAE and RMSE metric determine which gradient descent algorithm was optimal. For SOC and SOH prediction, the model developed an LSTM and BiLSTM model with four hidden layers and 128 LSTM or BiLSTM units per hidden layer using the NASA-released Panasonic 18650PF Li-ion dataset. The experimental results showed that choosing the optimal gradient descent algorithm had an impact on the model's accuracy. The issue of overfitting in the LSTM/BiLSTM model was also covered. Although it cost was higher, BiLSTM was the best option for enhancing the model's performance.

In 2023, Shibl et al. [15] proposed an ML-based BMS for SOC prediction and SOH estimation for unmanned aerial vehicles. This contribution is particularly significant because UAVs demand lightweight and high-efficiency power management due to limited payload capacity. UAVs are becoming more and more popular since they are employed in a range of industries, such as the military, agriculture, and research. Due to their low battery capacity, an appropriate BMS was required to minimize flight delays and crashes, which may be extremely expensive in terms of both time and money. SoH estimate and SoC prediction could extend the battery's lifespan and efficiency while assisting in ensuring that UAVs reach their destination. Because of the ML models' great accuracy, the findings confirmed their dependability. With a high explained variance score of 0.98 and a low MSE of 7.6E−4, the DNN model was used to estimate SoC. A high explained variance score of 0.97 and a low MSE of 0.023 were also observed in the SoC prediction produced with the LSTM model.

3.4 Hardware-Based BMS Systems

In 2023, Verani et al. [19] explained the construction and evaluation of a low-cost, modular multi-cell battery emulator that offered full cell voltage, temperature, and current simulation. This modular design allows researchers to replicate complex multicell interactions in a controlled environment without risking actual cell degradation. This platform might be used for hardware-in-the-loop testing on both commercial and custom BMSs. They discussed the main design and implementation choices, the results of the platform characterization, and the platform design constraints based on the most popular BMS designs. Comparing the proposed emulation platform to commercial and literary ones reveals a very good trade-off between cost and performance. The flexibility of the emulator made it suitable for testing a range of BMS configurations, from small-scale energy storage systems to large EV battery modules. Because of this feature, tiny labs that create and evaluate BMSs find it intriguing. This has led to the project being released as an open hardware platform that could be downloaded for free by the scientific community.

3.5 Digital Twin BMS

In 2022, Wang et al. [9] discussed the cloud-side end collaboration and digital twin technologies for the next BMS. A four-layer networked design of cloud-side-end collaboration for BMS enabled high-performance algorithms, overcoming the memory and processing power limitations of conventional battery management. The development of the battery's digital twin model allowed for improved and secure battery management during the battery's whole life cycle. This approach also made predictive maintenance possible by continuously synchronizing physical battery states with their virtual replicas. Further, the

digital twin paradigm and significant approaches like cloud-assisted battery equalization and condition estimation were presented. According to the findings, digital twin models were beneficial for managing batteries, and entire life cycle data could be used to develop a battery upgrade strategy.

In 2022, Jafari et al. [12] designed an electronic vehicle battery based on a digital twin, which might significantly improve BMS situational awareness and allow battery storage units to operate at maximum efficiency. AI and digitization create and present prospects. The XGBoost model and EKF were used in this model to predict the state estimation for the EV battery. However, the problem of onboard computing for the incremental SOH and SOC was addressed by DT. This effectively reduced the computational load on local devices by offloading complex estimations to cloud-based servers. The battery's condition was evaluated by the EKF, which also provided vital maintenance data. Therefore, DT models were useful for managing batteries, and full life cycle information was essential for organizing the battery's upgrade path.

3.6 Thermal Management & Cooling Systems

In 2021, Zhao et al. [6] proposed a two-layer predictive control strategy for warm/hot weather to address the aforementioned tradeoff. This two-layer architecture provides a balance between short-term temperature control and long-term energy efficiency. With the use of the look-ahead speed preview, battery power profiles, and the combined BTM and HVAC system efficiency surface from off-line data, the top layer controller first forecasts the ideal battery temperature trajectory. Subsequently, the bottom layer model predictive controller enforces the optimization of energy use while tracking the intended trajectory and cabin temperature reference. The coordination between these two layers ensures that passenger comfort and battery safety are maintained without excessive power consumption. Compared to a baseline control approach under typical driving circumstances and with a UDDS profile, simulation results showed that the proposed approach achieved up to 10.47% HVAC energy savings while exhibiting precise battery and passenger cabin temperature reference tracking. The proposed two-layer framework's practical implementation capacity was demonstrated due to the real-time vehicle emulator built on RCP and HIL platforms.

In 2024, Zhu et al. [13] examined the impact of several elements on the cooling performance of the Z-F composite structure BTMS, including the outlet's location, the number of steps, and the step surfaces' alignment. Their work highlights the structural optimization potential of composite designs for maximizing cooling uniformity while minimizing material cost. The findings showed that the outlet placement had a major impact on the cooling effect. Following outlet position optimization, the Z-F composite structure BTMS exhibited the lowest Maximum Temperature (Tmax) and Temperature Difference (ΔTmax). Tmax and ΔTmax were lower than those of the typical F-type BTMS by 1.14 ◦C (2.69 %) and 0.022 ◦C (1.10 %), and the Z-type BTMS by 2.69 ◦C (6.13 %) and 2.565 ◦C (56.51 %), respectively. When there were seven steps and the step surfaces were level with the right side of the cooling channels, the Z-F composite structure BTMS performed at its optimum in terms of cooling. This was ascertained by altering the number and time of the steps. The pressure drop increases more slowly between 2 and 4 m/s; the optimal input air velocity was 4 m/s. In conclusion, the Z-F composite structure BTMS demonstrated exceptional cooling performance under a range of operating conditions and held significant promise for practical applications.

In 2023, Luo et al. [11] proposed a numerical analysis of a BTMS using a liquid cooling plate in the shape of a square spiral ring. This unique SSR design enhances convective heat transfer efficiency by optimizing fluid circulation paths within confined spaces. The high local temperature of the battery was obtained in this work by designing a centrally dispersed SSR mini-channel liquid cooling plate for power batteries to reduce the temperature gradient effect. This liquid cooling plate BTMS was examined numerically by compressing the battery model. The results indicated that increasing the SSR channel laps and decreasing the channel width might optimize the temperature distribution of the battery and liquid cooling plate. By raising the inflow mass flow rate, it was possible to increase the uniformity of the battery temperature distribution and significantly reduce the maximum battery temperature. Furthermore, more branch channels could enhance the battery's gradient effect and temperature distribution uniformity. The maximum temperature and maximum temperature difference drop to 33.63 and 6.45 °C, respectively, when discharged at 2 °C in an ambient temperature of 25 °C.

In 2021, Wang et al. [18] proposed a parallel plate that increases the BTMS's cooling effectiveness, which could alter the battery pack's airflow distribution. The proposed airflow optimization strategy sought to reduce localized hotspots, thereby enhancing battery longevity and performance consistency. Initially, the impact of parallel plate count on BTMS cooling performance was investigated; the model with two parallel plates has the highest cooling efficiency and lowers Tmax and ΔTmax by 2.42 and 3.46 K, respectively, within the permitted range of power consumption loss. The impact of parallel plate length and height was then investigated; the optimal values were 1.5 mm for length and 30 mm for height. Finally, utilizing the aforementioned results, three optimization strategies were created for the model with

four parallel plates. This showed that the above conclusions were feasible and effectively increased the battery pack's cooling efficiency. After optimization, Tmax and ΔTmax are less than the original model by 3.37 K (6.17%) and 5.5 K (71.9%), respectively.

Table 1 shows the comparison of various surveys for BMS with different categories. It gives the categorization of the BMS-based technologies in various papers, which mention the surviving papers' achievements, methodologies, and future scope, respectively. This comparative overview helps synthesize the key technological advancements, providing a holistic understanding of emerging BMS research directions and design trade-offs.

Table 1. *Comparison of Various Surveys for BMS With Different Categories*

Categorization of BMS survey papers	Citation	Methodology	Achievement	Future Scope
IoT-Based Battery Management Systems	[1] [2] [5] [16]	Linear Programming and Simple Descent, ORMeshNet, CHAIN, OMnet++-based framework for LoRa (FLoRa)	Real-Time Monitoring and Control, Fault Tolerance and Redundancy, and Scalability	Communication Reliability, Power Consumption, Latency and Issues
Cell Balancing Techniques	[7] [17] [14]	Analogue Front End (AFE), Switched-resistor passive balancing-based method, Single-Ended Primary-Inductance Converter (SEPIC) DC-DC converter, Machine Learning (ML) based balancing control algorithm.	Low Power Consumption, Enhanced Safety, Cost-Effectiveness, Enhanced Performance Optimization, Cost-Effective in the Long Run	Limited Payload Size, Slow Balancing Rate, Accuracy Depends on Measurement Resolution, Computational Load
ML/DL algorithms	[3] [4] [8] [10] [20] [15]	Hybrid diagnostic frameworks integrating model-based and ML techniques, UAV BMS-ML, LSTM/BiLSTM, IWHODL-BMS, IB-DRN	Improved SOC Prediction Reliability,	Latency Concerns
Hardware-Based BMS Systems	[19]	Modular Multi-Cell Battery Emulator	Early Fault Detection, Improved Safety and Reliability	Data Dependency, Complexity in Large Battery Packs
Digital Twin BMS	[9] [12]	Extended Kalman Filter (EKF), Digital twin technology, and cloud-side end collaboration, Extreme Gradient Boost (XGBoost) model	Predictive Maintenance and Fault Detection, Real-Time Monitoring	High Implementation Complexity, Cost Implications, Computational Complexity
Thermal Management & Cooling Systems	[13] [11] [18] [6]	Two-layer predictive control strategy, Z-F composite structure BTMS, square spiral ring-shaped liquid cooling plate, parallel plate,	Improved Temperature Uniformity, Enhanced SOC/SOH Estimation, Cost-Effective, Energy Efficiency Improvement	Energy Consumption, Model Complexity, Computational Requirements, Latency, and Real-Time Constraints

4. Analysis and Discussion

This section explains the accuracy, scalability, cost, response time, and dependability of each technique used in the performance evaluation. In particular, it aims to assess how effectively these parameters influence the real-time operation and stability of BMS frameworks under diverse environmental and load conditions. Numerous methods were used in a BMS process, each with a distinct function. These methods include temperature monitoring, voltage-based monitoring, current-based monitoring, ML, balancing approaches, DL, and cloud integration, in that order. In Fig. 1, the achievements and future scope of several strategies used in the BMS process are displayed in a bar chart. This visual representation helps to clearly illustrate how emerging digital frameworks outperform traditional monitoring systems in terms of adaptability and precision. To emphasize performance trade-offs, each approach is given a score between 1 and 5. Similarly, Table 2 provides a list of the comparison analysis of various techniques utilized by BMS. A higher strength rate of 90% was created by the IOT/cloud-based BMS technique in Table 2, whereas other approaches like ML, DL, voltage monitoring, and current monitoring achieved strength rates of 60%, 65%, 80%, and 85%, respectively.

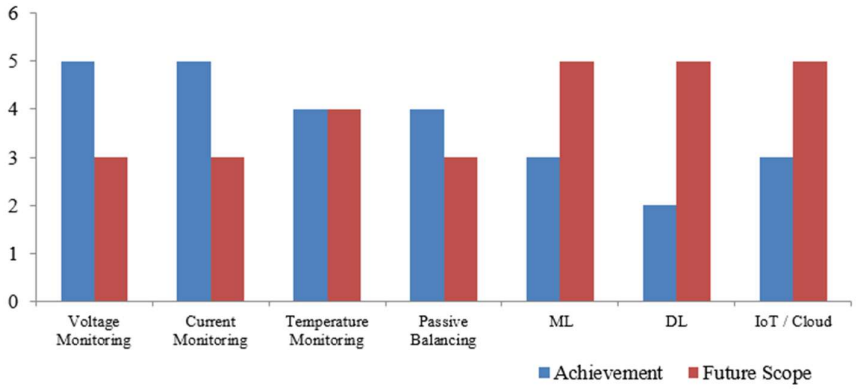

Fig. 1. *Comparison plot of achievement and future scope of the surveyed BMS-based approach*

Table 2. *Comparison Analysis of Various Techniques Utilized by BMS*

Technique using BMS	Achievement (%)	Future Scope (%)	Key Consideration (%)
Voltage Monitoring	60	40	55
Current Monitoring	65	45	60
Machine Learning	80	60	70
Deep Learning	85	70	80
IoT/Cloud	90	75	85

5. Research Gaps and Future Directions

(a) Shortcomings

- In dynamic situations, it may face the difficulty of effectively calculating SoH and SoC.
- Due to the heavy reliance on ECMs, the model is unable to adjust the batteries' nonlinear electrochemical activity.
- Advanced thermal management techniques are not completely covered, which increases the risk of thermal runaway and overheating.
- Several techniques are effective in small-scale laboratory experiments but ineffective in massive battery packs used in grid storage or electric vehicles.
- Real-time implementation is not feasible due to the high computational cost of sophisticated estimation/control techniques.

(b) Future Works

- **Advanced State Estimation:** Create hybrid SoC/SoH estimate techniques that combine AI, data-driven methodologies, and physics-based models for increased accuracy.
- **Electrochemical Modeling Integration:** Advancing from straightforward equivalent circuit models to capture nonlinear dynamics and informed by electrochemical/ physics.
- Cover the potential for applying other ML techniques, like reinforcement learning.
- **Aging-Aware Algorithms:** Produce BMS plans that accommodate second-life use and adjust to battery deterioration over time.
- **Fault-Tolerant Systems:** Create reliable problem detection and diagnostics to ensure safety in challenging situations (EVs, aerospace, grid storage).

6. Conclusion

This study offers an overview of BMS that have been implemented in various technologies, emphasizing the design difficulties, constraints, and opportunities for advancement. The review makes it clear that although there have been a lot of advancements in state estimation, fault detection, and safety processes, present BMS solutions still have issues with simplified modeling, poor thermal management, a lack of standardization, and difficulties with scalability in the real world. To guarantee the efficiency, safety, and longevity of batteries and also enable their sustainable practice in EVs, renewable energy storage RES, and other applications, the survey emphasizes the need for more comprehensive, intelligent, and scalable BMS systems. Future research on BMS should concentrate on hybrid modeling techniques that include data-driven and physics-based methods, battery longevity adaptive algorithms, strong thermal and fault management techniques, and cybersecurity-resilient frameworks for interconnected systems.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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