Enhancing Battery Health in Electric Vehicles: AI-Enhanced BMS for Accurate SoC, SoH, and Fault Diagnosis

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Abstract: Electric vehicles (EVs) are the only way to solve both harmful fuel emissions and other environmental issues. Safety, efficiency, and lifetime of electric vehicles depend on their battery management system (BMS), which is thus essential. Since internal resistance causes the capacity of the battery to drop with age, the BMS must continuously check its state. Reliable State of Health (SoH) as well as State of Charge (SoC) predictions call for more complex algorithms considering charging time, current, and capacity. Artificial intelligence (AI) driven methods increase the precision of diagnostics, the speed of issue identification, and the regulation of thermal management—all of which help to ensure the performance and safety of batteries. A malfunction diagnostic system offers further more protections. By means of successful use of these BMS algorithms, Energy Storage Systems (ESS) achieves effective control of battery capacity and long-term viability of operations of electric vehicles.

Keywords: Electric Vehicles, Battery Management System, SoC, State of health, Artificial Intelligence.

1. Introduction

Battery management systems are fundamental in electronic devices, energy storage, and electric vehicles to maintain their batteries working as they should. Maintaining an eye on key factors like current, temperatures, voltage, along with state of charge (SOC) helps one prevent thermal ran away, deeply departure, and overcharging. Timely and precise monitoring is essential for optimising performance and avoiding errors. Estimating parameters such as State of Charge (SOC), State of Power (SOP) and State of Health (SOH) are among the many tasks in battery management systems (BMS) that could benefit from advanced technologies. These tasks include cell balancing, defect diagnosis, and state estimation. Gaining useful insights into these factors is made easier using state estimation.

A BMS cannot function without cell balancing as it guarantees uniform battery pack charge. Approaching this procedure might be done either passively or aggressively. Enhancements in thermal control have enabled passive balancing—using heat to discharge extra charge. Activated balancing has been improved by means of power-efficient designs including high-efficiency capacitors and inductors, therefore enabling the redistributing of charge across cells. When it comes to fault identification—which is essential for locating and repairing battery system flaws—machine learning methods far surpass traditional model-based approaches. Hybrid methods that integrate machine learning and statistics have improved the accuracy of identification. Efforts are currently underway to develop real-time tracking systems to enable proactive problem management. Recent research has focused on combining AI and ML to enhance BMS decision-making and flexibility, resulting in better state assessment, fault identification and predictive maintenance. However, challenges remain in thermal control, algorithm performance, and system reliability. To improve system dependability and efficiency across different scenarios, it's crucial to explore new cooling techniques, materials, and optimize software for real-time applications.

This study attempts to clarify the present status of battery management systems by investigating developments in defect detection, cell balancing, and state estimation. There are several different BMS designs that may be used, each having unique advantages and disadvantages based on the battery's chemistry and arrangement.

2. Objective of the Study

This paper looks at the function of EV battery management systems, focussing on how they include sophisticated algorithms for problem detection, status estimate, and predictive maintenance. It examines how BMS may use ML, AI and temperature management to enhance battery performance, safety, and life. This study purposes to improve the efficiency and dependability of BMS across a range of operating scenarios by analysing methodologies and current technologies, identifying problems and offering solutions.

There are many gaps in what is already identified. To begin, although BMS approaches have advanced, there is still a need to optimise computing efficiency, particularly for complex non-linear systems. Secondly, thermal management is a major challenge, especially in extreme environments, and there are currently no obvious answers for improved cooling systems. Thirdly, in order to handle unanticipated anomalies, the system has to be more resilient, and it needs to be more reliable under different operating conditions. The fourth point is that BMS projections can only be as accurate as the datasets available, even when ML and AI are on the rise. Last but not least, emerging technologies like the IoT, computing via the cloud, and big data have introduced new security, privacy, and connectivity concerns, all of which need more study.

3. Battery Management System

By controlling the temperature, keeping tabs on the battery's health, and balancing the cells, the BMS considerably improves the battery's safety and health. By using advanced procedures and devices, a BMS is able to precisely track and control every cell in the power pack. This safeguards the battery against issues like over recharging, deep dripping, and excessive heat, which may significantly diminish its efficiency and lifespan. Enhanced dependability and proactive maintenance are two benefits of fault identification and predictive analytics, which are common features of contemporary BMS systems (Figure 1). As battery skill advances, the BMS becomes further intricate in an effort to keep up with the varying needs of various applications without sacrificing reliability, safety, or lifespan.

Figure 1 Modern BMS Systems

3.1 Types of Batteries

Different types of batteries composed of different materials allow chemical energy to be transformed into electricity. Modern electric cars use five main kinds of power sources: nickel-metal hydride, lithium-ion, supercapacitors, lead-acid and solid-state batteries.

3.2 Problems with Batteries

Problems illustrated in Figure 2 related to the battery management system might compromise the general performance of the vehicle. Regular charging and discharge cycles cause a battery degradation over time, therefore reducing the effectiveness, range, and overall capacity of a vehicle powered by electricity. Exceeding the battery's voltage can lead to overheating and thermal runaway. The Battery Management System (BMS) minimizes this risk by regulating charge rates and setting limits. Deep discharging shortens battery life and reduces charge retention. A modern BMS, with monitoring based on real time, adaptive procedures and comprehensive management, is crucial for efficient battery management. It uses advanced sensors, predictive analysis, and strong security measures to enhance performance, extend battery life, and ensure safety.

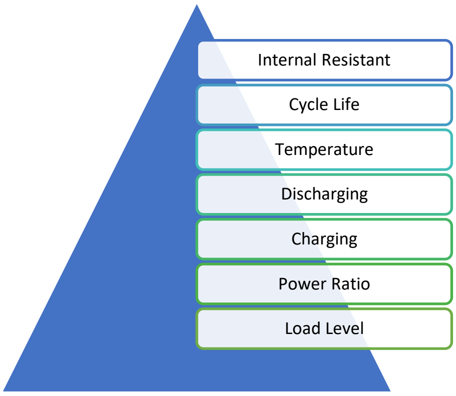

Figure 2 Battery-Affecting Factors

Thermal management is fundamental in battery management systems as it helps to maintain batteries efficient by preventing thermal runaway or breakdown under too high temperatures and performance loss under too low temperatures. HVAC systems and detectors help the building management system (BMS) to regulate the temperature. Cell imbalance, in which case the charging and discharging rates of every cell in a battery pack are not balanced, may also cause regularity and battery life issues. Since voltage variations may potentially compromise performance, the BMS has to continuously monitor and modify voltage to prevent harm. Though it may shorten battery life and generate heat, slow charging is milder than fast charging. The BMS needs to balance charging speed for lifetime and best efficiency. The BMS uses advanced algorithms to find abnormalities during actual time and provide maintenance alerts. The method has to be adjusted to maintain accuracy as internal resistance increases aged the battery. Two other environmental factors that could shorten battery life are extreme temperatures and excessive humidity; the BMS has to have precautions against these.

3.3 Battery Pack Cell Balancing

Cell balancing is a helpful regulating mechanism to maintain voltages, states of charge, states of power, and states of energy (SOE) of the individual cells of the battery pack within reasonable ranges. These variances might have detrimental effects on capacity for storing and battery life. For completely charged cells, charge, current, and electricity drop; for overloaded cells, all three drop as well. Hardware like chargers and tracking systems as well as software watching over everything manages this operation. The BMS circuit consists of balancing resistors as they help to sustain a constant voltage and prevent overcharging.

3.4 Unbalanced Charging

The repetitive charging and discharge cycles of a lithium-based battery weaken its stability by varying individual cell charge levels. Changes in chemical composition, temperature and starting charge states among other factors help to explain this discrepancy. The lifespan of a battery decreases as the discharge restrict of any cell approaches total exhaustion. Likewise, the whole pack has to halt to prevent harm if a cell gains full charge. This study delves into the ways in which the BMS solves these problems by prolonging battery life, enhancing energy efficiency and balancing cells. Electric vehicles need dependable fault management and battery safety diagnostics as even minute mistakes might derail a charge. Performance drops and safety issues arise when sensors for voltage, current, or temperature fail, which affects state estimates, interrupts thermal management, and disables battery equalisation. Problems with the actuator, such as blown fuses, broken contactors, the man bus, loose connections, or overheating cooling systems, may lead to higher resistance, more heat, and dangerous situations like battery terminals melting. The risk of thermal runaway increases when cooling is inadequate. Batteries may overheat, overcharge, over-discharge, short circuit, swell, leak electrolytes, and thermal runaway, which can induce adverse effects or gases that compromise safety.

3.5 Challenges and Foresight

The advancement of carbon neutrality and the replacement of gasoline cars with electric vehicles (EVs) are dependent on high-energy batteries for automobile propulsion, however these batteries encounter many obstacles concerning safety, rapid charging, and energy density. For efficient propulsion, a high energy density is necessary for both acceleration and range, and rapid charging seeks to achieve 80% capacity in minutes. Energy density must not be compromised in order to guarantee safety. There will be an emphasis on lithium-ion (LIB), lithium-metal (LMB), and other options, such as sodium-ion, in the development of future battery technologies. To address the demands of electric vehicles, scientists are working to improve LIB chemistries, solid-state batteries, and alternatives to lithium that have a lifespan of at least 10 years and can withstand 2000 cycles. Better optimisation of performance is another benefit of sensor-on-chip technology that will be available in Battery Management Systems (BMS).

4. BMS Optimisation Methods

4.1 Assessment of Current SOC

The State of Charge (SOC) of a battery is the ratio of its theoretical capacity to its present accessible capacity. Typically, SOC is expressed as a percentage using the following equation:

$$\mathrm{Q\ remaining\ SOC} = \mathrm{Q\ Total} \times 100\%$$

An objective physical metric is not possible for State of Charge (SOC). It is critical to precisely estimate the current SOC of a battery system to ensure it delivers its full measurements and to reliably predict remaining driving range. The BMS uses SOC to determine SOH, SOP, charge currents, and battery balance, among other things. Estimates of state of charge (SOC) have been more accurate since the 1980s. Methods for estimating state-of-charge (SOC) onboard include ampere-hour integral calculation, lookup tables, and method based techniques. Figure 3 displays the respective ways in which these strategies enhance the management and performance of the battery system.

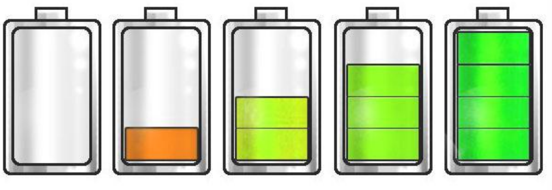

Figure 3 SOC Management and Performance of the Battery System

4.2 Health Status Prediction SOH

The State of Health (SOH) assesses the capacity of a used battery cell in comparison to a fresh one, which gives information on the battery's capability to fulfil operating requirements. One cannot evaluate the state of a battery or predict when it may need replacement without SOH. Feed forward algorithms, recurrent neural networks, entropy-based methods, regression and probabilistic approaches, and others may forecast SOH in lithium-ion batteries. A fresh battery has a SOH value of 100%, and as the battery ages, the SOH value lowers. The state of health (SOH) of the battery may be used to assess its present condition and estimate when it may need replacement.

4.3 State of Energy

SOE compares the battery's residual energy to its extreme or useable energy. Figure 4 estimates this using the entire battery charging and discharge cycle.

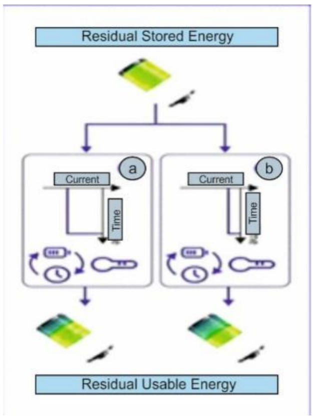

Figure 4 Battery Charging and Discharge Cycle

4.4 State of Power

The State of Power (SOP) displays the highest power that a battery can handle for a certain application, as seen in Figure 5. Operating voltage, temperature, and discharge all have an impact on SOP.

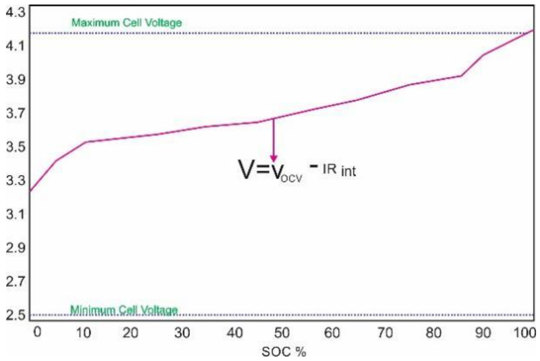

Figure 5 Battery Behaviour Under SOP.

Multiplying the operating voltage by the maximum discharge current yields an approximation of SOP. Changes to the rated current and degradation of the battery might cause SOP to alter. To build better Battery Management Systems, this method enhances measurements.

$$P = U \times I$$

4.5 Algorithm for Self-Discharge

Leaving a battery in an open circuit causes it to self-discharge, meaning it loses capacity. The capacity retention of a battery may be seen by measuring its self-discharge rate (SDR). The mechanism determines whether self-discharge is irreversible or not.

4.6 Thermal Management

Improving the efficiency of electric vehicles (EVs) relies heavily on controlling the temperature of their batteries. Uncontrollable exothermic processes, known as thermal runaway, may happen when temperatures reach dangerously high levels. Any temperature over 90 degrees Celsius will cause the electrolyte, cathode, and SEI layer to degrade. The minimal heat emission compared to another sorts of lithium-ion batteries is a remarkable attribute, especially of LiFePO4 batteries. Researchers have shown that when temperatures climb between thirty and forty degrees Celsius, the lifespan of a battery might be reduced by half. Optimal temperature control of batteries relies on efficient thermal management systems (TMS). Every cell in the battery operates within its designated temperature range, which is controlled by the TMS. The TMS will activate either the cooling or heating systems to safeguard the batteries and ensure safe operation when temperatures reach acceptable levels. Proactive management is able to prevent damage and overheating.

4.7 Life Prediction Remains Useful

Predicting the quantity of cycles under load or the duration it maintains efficient operation are two ways to determine the RUL of a cell of a battery. When making choices in real-time, such when to correct issues, RUL is a crucial measure to consider. Predicting RUL with any degree of accuracy, however, is not always possible because of all the unknowns. Machine learning techniques, time series analysis, statistical data-based methods, simulations using Monte Carlo, and other methodologies are some of the ways that RUL may be estimated.

5. Integrating IoT and Cloud Computing for BMS

Big data platforms, computing cloud and storage on the cloud all work together to make AI algorithms and controllers in BMS more reliable and efficient. Improved analytical methodologies and massive storage, processing, and analysis are made possible by big data technology, as seen in Figure 6. These technologies allow for the continuous monitoring and storage in the cloud of critical battery properties such as state of charge (SOC), state of health (SOH), RUL, thermal instability, and defect identification. The data will be pre-processed before being evaluated by the battery control and monitoring centre, who will then provide insights and recommendations for future enhancements. Concerns around privacy, security, interconnection, scalability, data management, standards, and regulations arise when the

Internet of Things (IoT) is linked to computing cloud. Consequently, these topics need further research.

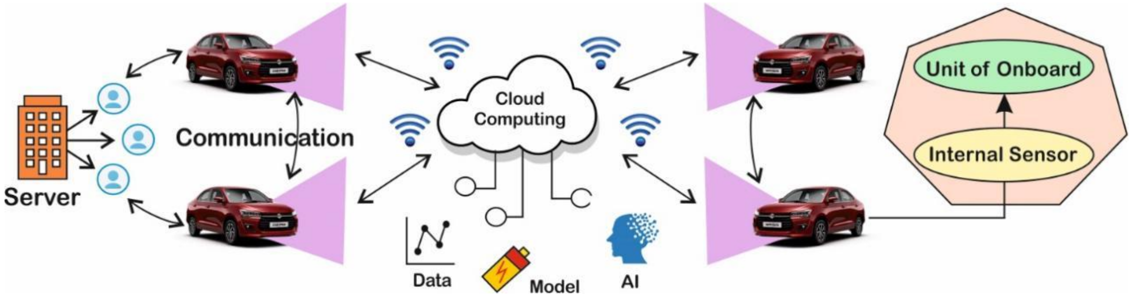

Figure 6 Integration of Computing Cloud and IoT

The IoT speeds up cloud data transfer, making battery system digital twins possible. These digital versions use diagnostic algorithms to check battery charge and age. Mobile and stationary field experiments have shown the viability of cloud-based battery management solutions. Problems with cloud computing-based energy scheduling solutions include the need for a lot of CPU storage, restrictions on local storage, and the need of a network.

6. Machine Learning Methods for BMS

The fundamental goal of ANNs is to simulate how the brain proceeds information. The incoming data is processed by the primary hidden layer using activation functions. After that, every neurone computes a weighted overall and sends it on to the subsequent layer. This procedure is carried out by use of a series of concealed layers, the last of which creates a forecast or outcome. A broad variety of applications may benefit from ANNs because of their exceptional adaptability and efficiency in tackling complicated problems.

6.1 Feed Forward Neural Net

A feed forward neural system is a simple kind of artificial neural network in which input data passes via a sequence of hidden nodes to output. This architecture guarantees that knowledge can only move in one way by removing incremental procedures and loops of feedback from the links between nodes. The performance of a network depends on the number of layers, neurone density per layer, and activation mechanism used. Because they can replicate complicated input-output interactions, FFNN are excellent for feature, prediction, and classification extraction. Their sluggish learning rates follow from their use of gradient-based training methods. FFNNs may lower computation needs and error margins by monitoring battery voltage while it charges. They calculate the SOH via discharge voltage entropy considering patterns in voltage fluctuations and battery degradation. Monotonic input feature constraints help to get better FFNN generalisation. Advanced FFNN designs are more efficient than more traditional ones. Integration of FFNNs into battery methods helps researchers to shorten training time and solve regional minima in SOC as well as SOH calculations. For low-power embedded systems, like electric car Li-Ion battery SOC prediction, this method works well.

6.2 Deep Neural Network

Deep Learning (DL) makes use of ANNs to identify complicated data features. This approach is particularly useful for assessing the State of Health (SOH) of the battery with varying starting SOC and C-rate currents. We find distinct temporal periods from 100% SOH to 80% SOH. Estimation in battery management often involves taking the first-order derivation of the discharge curve. The use of DNNs, or deep neural networks, allows for the optimization of estimates. The State of Charge (SOC) estimations and management methods for lithium-ion batteries have been improved with the development of several DNN models and learning techniques. The number of hidden layers used by SOC estimate models for EVs varies, but in general, more layers mean lower error rates and better accuracy. This works wonders when used with training data that contains lithium-ion batteries that have been subjected to different temperatures and loads throughout driving cycles. More accurate state-of-charge (SOC) evaluations and quicker convergence are outcomes of newer models that avoid overcharging and over discharging. Also investigated are non-electrical properties, such as capacity loss due to repeated charging and discharging. By manipulating charge and discharge settings, DNNs can forecast the RUL.

6.3 Convolutional Neural Net

Convolutional neural networks (CNNs) are being used more and more by battery management systems to forecast systems' states. In this network, every hidden layer has convolutional, pooling, fully connected layers. CNN are multilayer perceptrons. Utilising voltage, current, and charging capacity derived from partial charging cycles, they quantify the State of Health (SOH) of Lithium-Ion Batteries (LIB). CNNs improve prediction accuracy, decrease memory consumption, and accelerate testing. Especially in cases with unpredictable ageing and difficult operating circumstances, a CNN model with previous training may be applied to a microcontroller using STM32Cube.AI, allowing for real-time SOH estimate. New research on electric vehicle transfers learning and noise effect assessment using one-dimensional convolutional neural networks (CNNs) is available. Remaining Useful Life (RUL) estimate, predictive maintenance, hyperparameter optimisation, and network performance optimisation are common applications of convolutional neural networks. The security and dependability of Battery Energy Storage Systems (BESS) are enhanced using CNN methods, which identify defective battery balancing circuits with an accuracy of 96.32% and a high F1 score.

6.4 Recurrent Neural Network

The capabilities of Feedforward Neural Networks (FFNNs) may be expanded by a specific form of neural network design called Recurrent Neural Networks (RNNs). They are perfect for processing data in sequence because they can keep the context of the past intact. When working with interdependent sequences over lengthy periods of time, RNNs may encounter the long-term dependency problem. One way to manage the complexity and variety of input signals and improve method performance is using sparse sampling. Data compression allows for accurate representation of battery properties, while optimisation methods that take use of signal sparsity allow for the recovery of critical information from sparse datasets. Optimising network architecture for simpler online deployment is crucial for LSTM technique enhancement. Assisting in the prediction of long-term capacity deterioration, RNN when used to the modelling and estimate of State of Charge (SOC) for lithium-ion batteries capture complicated non-linear behaviours and resolve gradient concerns. Additionally, RNNs are capable of estimating the RUL for health monitoring purposes in aero-engines.

6.5 ML Algorithms

A more accurate digital representation of batteries is now possible because to the widespread usage of sensing equipment and the rapid development of Internet of Things (IoT) devices, which have made data collection much simpler. The use of radial basis functions, support vector machines, recurrent neural networks and machine learning is on the rise.

7. BMS Challenges and Issues

Algorithms, deployment, and data management are three areas where Battery Management Systems (BMS) encounter difficulties. Optimisation approaches, recurrent neural networks and deep learning improve performance, but their high processing and enormous dataset needs may be burdensome for high-dimensional or nonlinear networks. Statistical approaches like entropy and Monte Carlo take a lot of energy and have slow convergence. Implementing a BMS requires accurate sensors, ambient management, and thermal management to minimise overheating. Validation is needed to meet safety standards, and integrating the BMS with other systems may delay development and increase costs. Since BMS handle enormous amounts of temperatures, voltage, and current sensor data, data processing is another issue. Advanced algorithms and machine learning are needed for data processing, linking, software and hardware interoperability, and battery performance optimisation. Battery chemistry, ageing cycles, and degradation all have an impact on BMS accuracy, which in turn causes various state estimates and problems like thermal runaway. If they want electric car and other technology batteries to last longer, be safer, and work more efficiently, we must solve these problems.

8. Conclusion

Efficient and well-designed battery management systems are essential for the future of electric vehicles. The increasing complexity and demands placed on EV batteries need the development of more sophisticated BMS capable of accurate prediction of SOC, SOH, and RUL. Machine learning and artificial intelligence have the potential to enhance the accuracy and reliability of these estimates in dynamic operational environments, as stated in the research. Improving the safety and lifetime of the battery system, the BMS's robust fault detection algorithms find potential flaws early on. Preserving the performance and safety of batteries requires advancements in cooling technologies and materials. By enabling real-time monitoring and predictive maintenance, cloud computing and the internet of things enhance BMS capabilities. The paper comes to the conclusion that in order to keep up with the demands of the electric vehicle industry, handle the latest battery technology, and help make transportation more sustainable, BMS technologies need to be studied and created.

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