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Sensor Technology for Improving the Safety and Performance of Electric Vehicle Battery Management Systems

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Abstract: With the rapid development of electric vehicles, the safety and performance of battery management system (BMS) has already become a worldwide problem. The performance, life and safety of a car battery have a direct impact on the overall reliability and user experience of the car. This paper discusses the application of advanced sensor technology to improve the safety and performance of electric vehicle BMS. The influence of different kinds of sensors, such as temperature, voltage, current and gas sensors, on real-time monitoring, failure detection and battery performance optimization were discussed. It also explores the potential of sensor integration, predictive maintenance and smart charging management for accurate estimation of state of charge (SOC) and state of health (SOH). The study indentified important challenges regarding the regarding the precision, cost and environmental adaptability of sensors and suggested the future direction that can meet the needs of the nesxt generation BMS systems. This study provides insights that could enhance the safety and efficiency of BMS through sensor technologies critical to the performance and safety of future electric vehicles.

Keywords: Battery Management System; Electric Vehicle; Sensor Technology.

1. Introduction

The global shift from fuel vehicles to electric vehicles is one of the most important strategies to reduce carbon emissions, combat climate change and promote sustainable energy [1]. As a core component of electric vehicles, batteries are at the heart of this shift. However, the safety and efficiency of batteries remains a major challenge. The battery (BMS) is made up of ceramic microcircuit enclosures designed for battery safety, from, for example, temperature and on. (SOC) how the battery overheats and space and center issues before charging, all of which affect the car, safety and film.

As the demand for electric vehicles grows, BMS technology is becoming increasingly important. The battery is the most expensive component of an electric vehicle, ensuring its safe operation. BMS technology has developed a variety of sensors to monitor battery parameters in real time, detect gaps, and ensure efficient performance. Highly intelligent sensor technology is integrated to accurately monitor voltage, current, temperature and even battery emission to improve the safety and efficiency of the entire system. Sensors play a crucial role in predicting the state of charge (SOC), state of health (SOH), and remaining life (RUL) of a battery.

While the integration of the sensors has greatly improved the performance of the BMS, there are still some unresolved issues, especially regarding the accuracy and reliability of the sensor data and the optimal integration of the sensors with the armored forces. These issues can lead to poor battery management, resulting in reduced battery performance, safety risks, and longer life.

Over the past few years, many studies have used sensor technology to improve the accuracy of BMS. Some research has focused on developing more accurate and reliable sensors for temperature, volt, and current measurements. For example, the Wangs achieved a lifespan prediction of lithium-ion batteries based on various extracted features and gradient boosting regression tree model, which meant they did a better job of correctly estimating SOC and SOH [2]. Similarly, Milad Bahrami and others have developed a multi-measurement system which used Polymer Electrolyte Membrane Fuel Cells to reduce the risk of heat waves, a major safety concern for lithium batteries [3].

While these improvements have increased the functionality of BMS, studies to date have left some gaps. For example, most existing sensors cannot detect a variety of potential hazards that are usually only detected in the event of a serious failure, such as a gas light or premature charging. In addition, the accuracy of SOC and SOH estimates is still limited, especially in complex battery layouts where the behavior of individual cells can vary greatly.

Despite promising advances in integrated sensors, issues such as cost, convenience and the ability to operate reliably in extreme conditions remain hidden in the background. The need for better multi-sensor data integration technologies that can provide more accurate and predictable battery management is another area of research that is still evolving.

While these improvements have increased the functionality of BMS, studies to date have left some gaps. First, there is a lack of many existing BMS to explain the complex nonlinear behavior of modern lithium batteries [4]. Second, piezoelectric sensors are not well adapted to the environment and are not reliable under certain conditions, such as extreme temperature or humidity [5]. Third, it lacks an integrated approach to integrate real-time data from different sensor types to predict battery failures before they occur [6].

These vulnerabilities present new opportunities to improve the security and quality of BMS. New, more reliable sensors and data consoles may overcome these problems.

The purpose of this study is to discuss the latest advances in the field of sensor technology to improve the safety and performance of electric vehicle systems.

2. Traditional Battery Management Systems and Sensor Technologies

2.1. Battery Management System Overview

Battery management (BMS) is an important part of electric vehicles, responsible for battery health, performance optimization and vehicle safety. BMS from information to battery, state and SOH generated by electricity, current, temperature, storm and storm return to secure access. With the proper parameters, BMS can protect the safety of the battery, such as preventing overload or overheating, thereby improving the safety of the vehicle and extending the battery life.

Over the past few years, BMS have evolved from single voltage or temperature sensors combined into more complex models with multiple sensors to collect and predict real-time data. These advances are critical to improving the overall performance of electric vehicles, as they directly affect battery efficiency and life.

2.2. The Role of a Single Sensor in a Battery Management System (BMS)

Sensors are an integral part of BMS. They provide the necessary data to monitor battery status in real time. Common device types include temperature, volt, motor, and gas sensors, all of which have their own effects, but also have drawbacks when it comes to safety and optimizing battery safety.

2.2.1. Temperature Sensors

Lithium batteries are very sensitive to temperature fluctuations; Due to overheating, the temperature is distorted again and the service life may be affected. Multiple temperature sensors are used to monitor different positions of the battery. Studies have shown that temperature anomalies can be detected using distributed temperature sensors to prevent the risk of lithium batteries overheating [7].

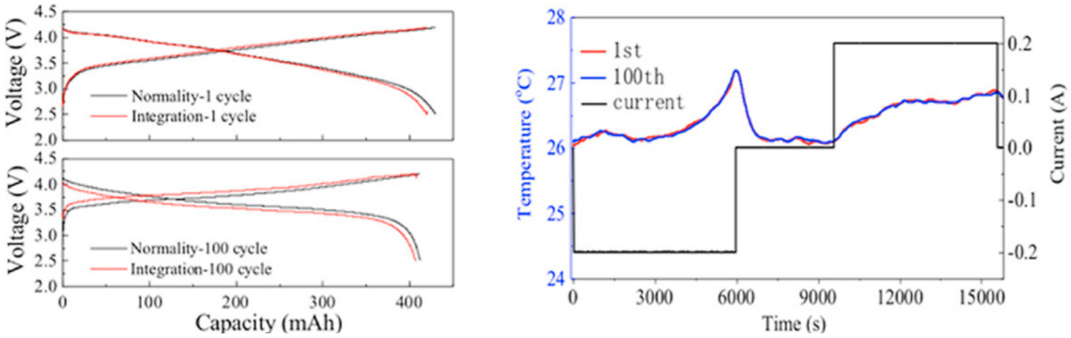

Figure 1. Multi-point temperature sensor network for thermal management of lithium-ion batteries (Li et al., 2019).

2.2.2. Current Sensors

Current sensors play an important role in calculating the state of charge (SOC) and state of health (SOH) of Li-ion batteries. Toward a smarter battery management system: A critical assessment of optimal charging methods for lithium-ion batteries, the accuracy of current measurements directly affects the SOC estimated by the Coulomb counting method. Their analysis showed that a high-precision Hall-effect current sensor (error ±0.2%) reduces the SOC estimation error to 3%, compared to 8% (error ±1%) for a conventional shunt resistor [8].

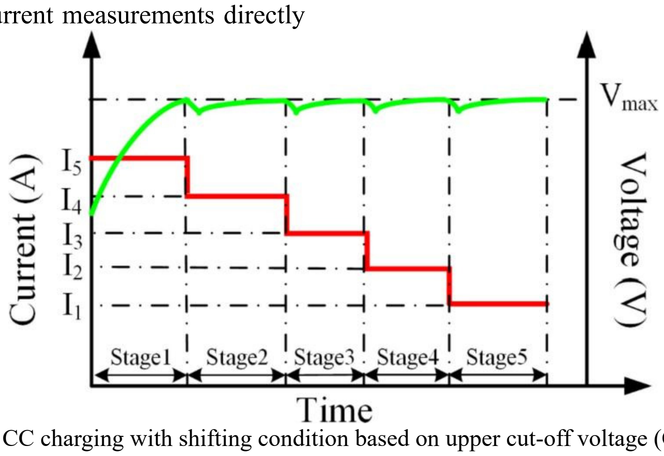

Figure 2. Five-stage CC charging with shifting condition based on upper cut-off voltage (Qian Lin et al., 2019)

2.2.3. Gas Sensors

Gas detectors are crucial for identifying the solid state of these batteries, such as CO CO2 and C2H4, which are often the result of battery replacement. With the integrated real-time BMS, passengers can identify unexpected changes in concentration before failure, taking advantage of the gas potential generated in the control room for increased safety [9]. Gas sensors are used in conjunction with temperature or current sensors to provide additional protection.

3. Sensor Integration and Data Fusion

3.1. Challenges of Current Sensor Technologies

While this improved sensor technology may help BMS, there are still some challenges. One of the most important issues is the accuracy of individual sensors, especially compared to the large battery systems that run on electric vehicles. Existing models, based on traditional estimates, often fail to explain the behavior of individual cells in battery stocks. Recent studies by Wang et al. demonstrate that cell-to-cell variations in large battery packs can lead to up to 15% estimation errors when using conventional sensor configurations [10].

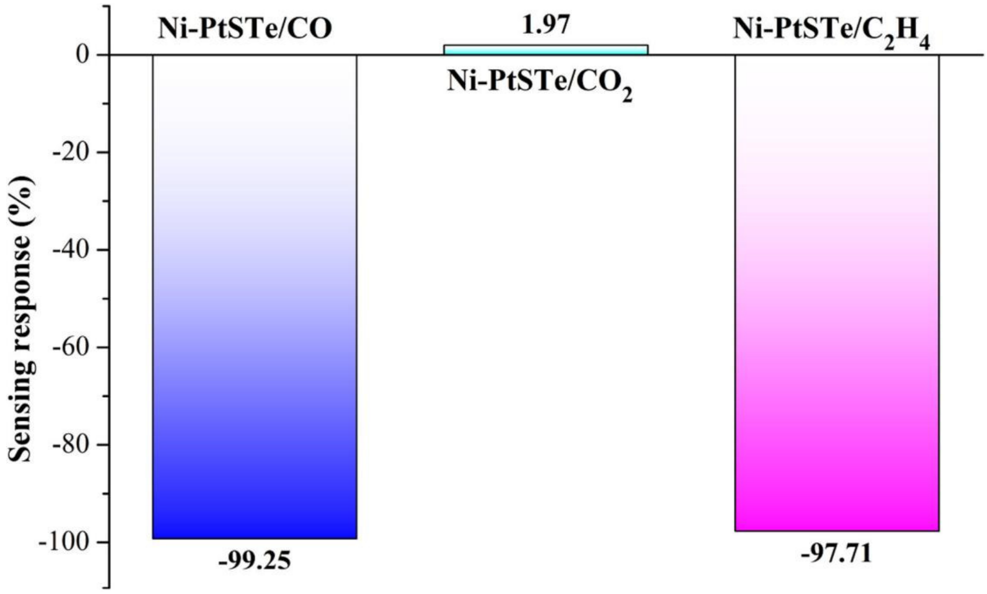

Figure 3. Sensing response of Ni-PtSTe upon CO, CO2 and C2H4 at room temperature (Dan et al., 2024)

And, because of the mobility of the vehicle, adapting the sensors to the environment remains a problem. For example, during driving, very extreme temperatures or high vibrations can cause sensors to fail, reducing the accuracy of the test. To address these issues, new sensor systems must be able to operate under extreme conditions, such as temperature, humidity, and vibration.

Another challenge is the cost of high-precision images. Many of the most advanced sensors, such as gas sensors and multi-point temperature sensors, ensure the low-cost use of electric vehicles in the general market. As the research by Nishi et al. indicates, advanced battery monitoring sensors currently account for 12-18% of total BMS costs in commercial EVs [11]. As the research shows, developing cost-effective and highly accurate alternatives is critical to facilitating access to these technologies.

3.2. Multi-sensor System in Battery Management Systems

The advanced BMS uses multiple sensors that incorporate different types of sensors to measure the health of the battery (e.g. voltage, temperature, current, gas emissions). However, by incorporating these sensors, the system can detect faults of all kinds that cannot be detected with a single type of sensor. Gas detectors, for example, are of crucial importance in order to detect gases emitted or overcharged by a battery.

This combination of sensors provides a comprehensive view of battery health and therefore more efficient safety and performance management. One of the most efficient strategies to improve BMS, accuracy and safety would be to use a multi-sensor system that incorporates data from all types of sensors to provide a complete understanding of the battery's condition and health. Research by Feng et al. highlights that multi-sensor fusion (e.g., combining voltage, temperature, and pressure data) reduces SOC estimation errors by up to 40% compared to single-sensor approaches [12].

These systems combine temperature, current, gas and pressure sensors to monitor the various battery parameters, and they will increase the estimated accuracy of the SOC and the SOH, and it will be able to detect potential outages at an early stage [8].

3.2.1. Benefits of Multi-Sensor Systems

Embedding different types of sensors in a BMS could have a number of advantages compared to individual sensors.

To achieve the core, you first need comprehensive monitoring of the battery system: a multi-sensor system monitors the various parameters of the battery in real time, such as temperature, voltage, quantity of gases, internal pressure, etc. For example, temperature sensors receive information about overheating, voltage and current sensors the leakage and discharge behavior, gas sensors the first signs of battery damage, such as hydrogen discharge. By using these measurements, the BMS will gain a more accurate and complete understanding of the condition of the batteries, which will improve the SOC and the accuracy of the estimates [13]. Sensor redundancy reliability is supported by NHTSA's analysis showing 23% BMS failures originating from single-sensor errors [14].

Secondly, redundancy is an important aspect of BMS safety in terms of redundancy and reliability. The other sensors can provide backup to ensure the continuity and reliability of their performance in case a sensor malfunctions or provides incorrect data. For example, if the electronic sensors provide different readings, the BMS may rely on data from electrical and thermoelectric sensors to assess the SOC with sufficient accuracy [15].

Finally, multiple sensor systems can detect failure earlier than a single sensor system by combining data from different sensors. A sudden rise in temperature combined with lower or erratic gas emissions could be a sign of future faults, making a system capable of intervening early enough (for example, turning off the battery pack or a switch for cooling).Early intervention is essential to prevent a heat wave or other malfunctions[16].

3.2.2. The challenge of Multi-Sensor Systems

Although multi-sensor systems offer significant advantages, it would be difficult to integrate them into BMS. In terms of data synchronization, data may not be synchronized with other sensors and frequencies at the same time. Integrating data from different sources, especially in real time, may be a challenge. If the data is not properly synchronized, it can lead to a miscalculation of the memory situation, which affects the SOC and the accuracy of the estimates. Advanced algorithms are required to ensure that the measured values are correct.

As far as calibration is concerned, sensors, especially those that measure physical properties such as temperature or gas concentration, can go through the process of calibration. This can represent an error in the measured values, which affects the performance of a multisensor.

And finally, there is the issue of environmental sensitivity. The special conditions in which electric vehicles are located mean that several sensors react to a range of uncontrollable influences. Transmitter systems are usually installed in hostile environments with low electromagnetic interference, extreme temperatures or mechanical vibrations. These conditions will affect the performance of the sensors, especially those based on electrical measurements, such as the reverberation and wave indicators. Environmental factors such as humidity and atmospheric conditions will also affect the gases and temperatures, resulting in distorted data. To overcome these problems, the BMS will need to integrate conversion and interception technologies into the multi-sensor system.

3.3. Application of Data-Driven Technologies to Multi-Sensor Systems

As the concentration of sensors in the battery management system (BMS) increases, it becomes difficult to accurately calculate the state of the battery (SOC) and health (SOH) using single physics models alone [17]. The multi-sensor system stands for monitoring the battery status via sensors such as integrated temperature, voltage, electricity, gas and pressure. However, the challenge for current research is to extract useful information from infinitely large quantities and thus make the predictions more precise.

Data drive technology combines the learning of battery dynamic properties by learning from historical data and the real-world adaptation of its prediction models with statistical algorithms. In particular, the combination of the neural network (NNM) with highly advanced algorithms such as the Bakm filter (UKF) and the short and short-term memory network (LSTM), which are highly accurate and reliable.

3.3.1. Estimation Method based on the Combination of NNM and UKF

As the battery management system increasingly evaluates the SOC and SOH with accuracy, traditional methods based on mathematical models are increasingly challenged in a complex nonlinear environment. On the other hand, the nonlinear projection of the NNM (NNM), which is a non-backtracking of Karman filters (UKF), increases the advantage of the lis tracking and noise behavior of UKF, making the SOC and SOH contribute significantly to the accuracy and reliability of the measurements.

The fundamental principle of the NNM -UKF approach is as follows: NNM is a data-driven biometric modeling that affects the dynamic behavior and generation patterns of a battery such as voltage, current Or temperature. With the input, a data memory is entered, e.g. data (such as strength, current, temperature), then the sends out the SOC or the estimates of SOH via the nonlinear function (e.g. ReLU or Sigmoid). In training, the NNM/nm focused on adding weights and deviations by minimizing the differentiation function to obtain the nonlinear thermal model of the battery state.

The undetectable carelusierer is a method for determining the state of a nonlinear system that evolves a group of sigma through unlocalized changes and updates the state of the system through the carmalel line, thus predicting the distribution of the system.

3.3.2. Battery State Estimation Method Based on the Combination of Neural Network Model (NNM) and Unscented Kalman Filter (UKF)

And the NNM-UKF combination strategy is usually as follows: the combination of NNM and UKF usually adopts NNM as the state observer, while UKF is responsible for state tracking and noise filtering. Firstly, the NNM is used to build the SOC or SOH mapping model of the battery by training with historical battery data.The UKF receives the real-time sensor data (voltage, current, temperature) and performs the state updating based on the predicted values of the NNM and filters the sensor noise, and then corrects the error of the NNM output by the correction of the UKF.

The advantage of the NNM-UKF method is that the NNM can effectively learn the dynamic characteristics of the battery, while the UKF handles the nonlinear state estimation through the traceless transformation, avoiding the linearization error of the EKF [17]. Secondly, UKF performs well in dealing with sensor noise and environmental disturbances, which enhances the stability of SOC and SOH estimation. Meanwhile, UKF is capable of state tracking during battery charging and discharging dynamics, which realizes high-precision SOC and SOH estimation.

Under model mismatch conditions, Extended-KalmanNet computes KGs using neural networks that are closer to the EKF (matched) than the EKF (mismatched), allowing the Extended-KalmanNet algorithm to perform SOC estimation with higher accuracy under these conditions [18].

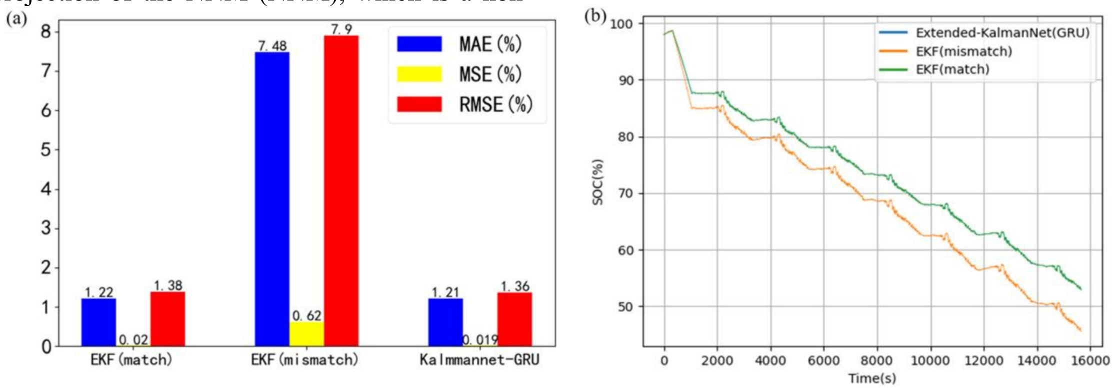

Figure 4. SOC estimation results under Laplace noise (UDDS): (a) Error; (b) SOC estimation results (Zhao et al., 2024).

The battery state estimation method based on the combination of NNM and UKF achieves high-precision SOC and SOH estimation by fully utilizing the nonlinear mapping capability of NNM and the real-time tracking and filtering advantages of UKF. The method has a broad application prospect in electric vehicles and energy storage systems, and future research will further optimize its computational efficiency and cross-platform adaptability.

The application of data-driven technology in BMS significantly improves the accuracy and stability of battery state estimation. By combining NNM-UKF method with the timing analysis capability of LSTM network, BMS can achieve high precision prediction of SOC and SOH under complex working conditions, and effectively extend battery life [19]. Future research will further promote the application of data-driven approaches in the field of battery management, providing strong technical support for the widespread deployment of electric vehicles and energy storage systems. The research by Jarraya et al. demonstrated that LSTM-based SOH estimation reduces error to 97.12% compared to 65.47% and 94.86% for SVR-LSTM and CNN-LSTM. These results confirm form the table that SOH-KLSTM achieves state-of-the-art accuracy while maintaining computational efficiency, making it an optimal solution for real-world applications, including electric vehicles and industrial battery management systems [20].

Table 1. Comparison of proposed SOH-KLSTM performance for SOH prediction with other models proposed in the literature (Jarraya et al., 2025).

Ref	B0005 dataset			B0007 dataset			
	Model	RMSE ↓ (%)	MAPE ↓ (%)	Error reduction ↑ (%)	RMSE ↓ (%)	MAPE ↓ (%)	Error reduction ↑ (%)
Obisakin et al. [30]	SVR-LSTM	0.003	0.30	94.86%	-	-	-
Ma et al. [20]	DEGWO-LSTM	0.325	0.467	–	0.377	0.423	–
Yao et al. [14]	LSTM	0.058334	5.83	–	0.041061	4.11	–
Zhu et al. [29]	CNN-LSTM	0.02	2.00	65.74	0.03	3.00	26.83
Lie et al. [63]	SBL	3.5656	–	–	2.6153	–	–
Yao et al. [62]	GPR	0.0114	–	–	–	–	–
Zhang et al. [64]	CMMOG	0.6490	0.4731	–	–	–	–
Chen et al. [65]	DGL-STFA	0.876	–	–	0.876	–	–
Proposed model	SOH-KLSTM	0.001682	0.17	97.12	0.002112	0.21	94.85

4. Conclusion

This study comprehensively investigates the application of sensor technologies in improving the safety and performance of Battery Management Systems (BMS) for electric vehicles. The analysis demonstrates that advanced sensor types—such as temperature, current, voltage, gas, and pressure sensors—play critical roles in real-time monitoring and early fault detection. Furthermore, multi-sensor integration and data fusion strategies significantly enhance the reliability of state estimations.

In particular, data-driven approaches like the integration of Neural Network Models (NNM) with Unscented Kalman Filters (UKF), as well as Long Short-Term Memory (LSTM) networks, exhibit high accuracy in estimating the State of Charge (SOC) and State of Health (SOH). These hybrid methods provide superior performance in dynamic and nonlinear environments, making them promising for future intelligent BMS.

However, challenges remain, such as sensor drift, data quality inconsistencies, high computational complexity, and the lack of model generalizability across different battery chemistries. Future work should focus on the development of robust, scalable sensor architectures, low-latency fusion algorithms, and the integration of edge computing to support real-time, intelligent energy management.

Overall, the effective deployment of advanced sensor systems and data-driven models holds the key to ensuring safer, more reliable, and longer-lasting battery systems, which are essential for the ongoing evolution of electric vehicles and energy storage technologies.

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