Overview of the Application Status of Power Battery Safety Warning Technology

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Abstract: The frequent occurrence of power battery safety issues has seriously hindered the healthy development of the new energy vehicle (NEV) industry. With the widespread use of power batteries, problems such as thermal runaway, overcharging, and aging failures have become increasingly prominent. Power battery safety early warning technology plays a crucial role in ensuring the safe operation of batteries by monitoring key operating parameters, identifying abnormal states, and issuing early warnings. This paper reviews the research progress and current application status of power battery safety early warning technologies, systematically analyzes the internal and external factors affecting battery safety, summarizes mainstream technical approaches including threshold detection, state of health (SOH) analysis, model-based prediction, and data-driven methods, discusses the existing challenges such as data quality, feature extraction, model generalization ability, and limited early warning accuracy, and looks forward to future development directions. It emphasizes improving battery safety management and lifetime prediction capabilities through advanced sensors, intelligent algorithms, and the "Terminal-edge-cloud" collaborative architecture.

Keywords: Power Battery; Safety Early Warning; Security Risk Assessment; Battery Management System; Thermal Runaway

1. Introduction

In recent years, the NEV industry has developed rapidly. As of the end of June 2024, China's national stock of new energy vehicles has reached 24.72 million units [1]. Power batteries mainly refer to batteries that use lithium ions as anode materials. As a key component of the new energy vehicle industry, they play a significant supporting role in its development. However, at present, safety issues related to power batteries occur frequently, causing huge losses to social welfare and affecting the development of the new energy vehicle industry.

To enhance the safety of power batteries, battery manufacturers, research institutions, and universities are all conducting research in areas such as intrinsic safety, passive safety, and active safety, as shown in Figure 1. Solid-state/semi-solid-state batteries eliminate or reduce the use of electrolytes, offering higher safety. However, key technologies still need to be broken through, the process is not yet mature, and the price is relatively high. Mass production is still some time away [2]. Optimizing the structural design of battery cells, enhancing the high-temperature and high-pressure resistance of the electrolyte and the strength of the separator can reduce the probability of thermal runaway caused by aging during use and improve the safety of the battery [3]. Improving the rationality and reliability of the battery pack structure design, enhancing thermal management level, mechanical protection strength, fatigue resistance and other aspects can help improve the safety of the battery pack. The use of thermal insulation materials helps to block the heat diffusion process between battery cells. Combined with thermal management to transfer heat, it can suppress thermal runaway of battery modules. However, it is necessary to balance the contradiction between thermal insulation and flame retardancy and energy density [4]. Optimize the design of the battery management system (BMS) and reasonably set the temperature and voltage range for battery usage. Improving its stability and avoiding battery control system failures can prevent the abuse of electric heating [5]. There are also many research and applications on active safety. Battery safety early warning is one of the important methods. Battery safety early warning refers to the status detection of power batteries based on battery operation data and the safety early warning for possible thermal runaway situations, thereby avoiding safety accidents. Battery safety early warning technology has been widely deployed in real vehicles due to its advantages such as convenient deployment, high computing efficiency, and wide coverage. This article will elaborate on the application of safety early warning technology, mainly divided into the following five parts: 1) analysis of thermal runaway factors; 2) application of safety early warning technology; 3) safety early warning system architecture; 4) current problems and challenges; 5) summary and outlook.

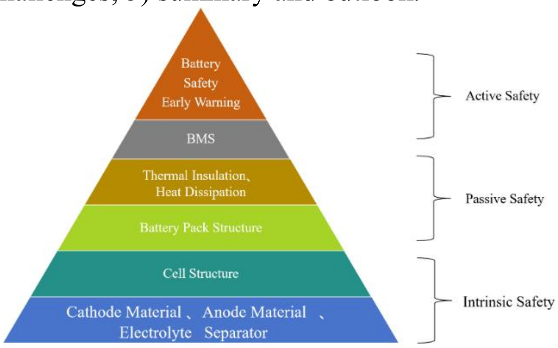

Figure 1. Research on Battery Safety

2. Analysis of Thermal Runaway Factors

Battery thermal runaway refers to situations where battery packs smoke, catch fire, or even explode. It involves a series of complex chain reactions. There are many factors that can cause battery thermal runaway, and the direct causes mainly include internal short circuits, runaway reactions, and external short circuits. Battery materials, process issues and aging during use are internal factors that cause loss of control. From an external perspective, it can mainly be classified into mechanical abuse, electrical abuse and thermal abuse.

A short circuit inside the battery and the contact between the positive and negative electrodes will generate a large amount of heat. On the one hand, this heat will accelerate the dissolution of the separator. On the other hand, when it accumulates to a certain extent, it will cause out-of-control side reactions, generating a large amount of flammable oxidation-reducing agents and releasing a large amount of heat at the same time, further aggravating the occurrence of thermal runaway. Out-of-control reactions refer to abnormal reactions that occur in materials such as battery separators, electrolytes, positive and negative electrodes, etc. These reactions can lead to material decomposition, heat generation and accumulation, and trigger chain reactions. When an external short circuit occurs in a battery, heat is generated. When the heat accumulates to a certain extent, it may trigger an out-of-control reaction and the dissolution of the separator, thereby leading to overheating and out-of-control [6].

The mechanism of battery thermal runaway is shown in Figure2, which can visually reveal the evolution process of energy accumulation and chain reaction under internal short circuit, external short circuit and various abuse conditions.

Mechanical abuse can cause wear or mechanical deformation of the battery structure, leading to external short circuits, and may also cause the separator to rupture, resulting in internal short circuits. Thermal abuse refers to the improper use of battery temperatures, causing the battery to overheat. High temperatures accelerate the decomposition of the separator, leading to internal short circuits. Electrical abuse includes situations such as improper voltage control and damage to electrical components. Low-temperature over-discharge can cause lithium dendrites to grow, piercing the separator and triggering an internal short circuit. Overcharging and other factors can cause the reaction to get out of control, leading to thermal runaway. When electrical components are damaged, it may cause an external short circuit.

During the use of batteries, they will gradually age, generating dendrites and the separator will gradually dissolve. Coupled with the influence of processes and materials, when the accumulation reaches a certain extent, it may cause an internal short circuit.

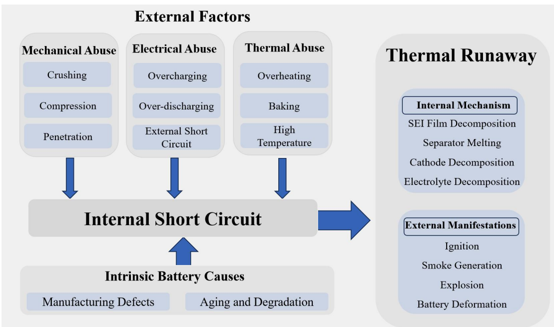

Figure 2. Mechanism of Battery Thermal Runaway

3. Application of Safety Early Warning Technology

When thermal runaway occurs in power batteries, there will be obvious changes in characteristic parameters, mainly including terminal voltage, surface temperature, current, internal resistance, internal temperature, capacity, state of charge, etc. During the risk development stage, these characteristic parameters of the battery will also have slight changes. Safety early warning is to issue early warnings and alarms for batteries by mining the subtle change patterns of characteristic parameters and detecting parameter changes that exceed the threshold.

The commonly used techniques mainly include: threshold detection, health degree analysis, internal short circuit analysis, lithium plating analysis, model-based methods, data-driven methods, and multi-model method fusion, etc.

The classification of battery detection methods is shown in Figure3, which comprehensively presents various detection methods and their application frameworks in safety early warning technology, covering both traditional detection techniques and innovative methods based on battery models.

3.1 Threshold Detection

Threshold detection is often used for the detection of data such as voltage and temperature, and it has the characteristics of simple calculation and rapidity. The BMS deploys threshold detection algorithms to issue minute-level alarms in the early stage of an accident, facilitating personnel evacuation and timely handling. However, When the parameters exhibit obvious characteristic changes that reach the threshold, the accident is often already on the verge of occurrence. To advance the early warning time to the daily or even monthly level, it is necessary to start from historical data, explore the patterns of subtle feature changes, identify early abnormal batteries, and take proactive measures before accidents occur.

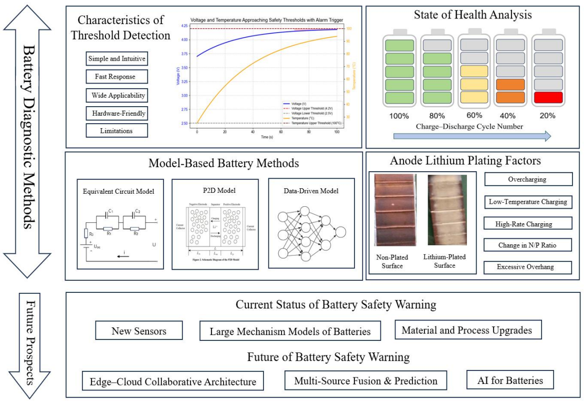

Figure 3. Summary of Methods for Battery Detection

3.2 SOH Analysis

The SOH of power batteries has a certain relationship with safety. The greater the degree of degradation, the greater the safety hazard. Paying attention to the degradation state and rate of batteries can, to a certain extent, screen out abnormal batteries. There are many aspects related to health, such as capacity retention rate, discharge capacity, internal resistance, etc. Currently, capacity retention rate is mainly used for characterization, and its calculation method is based on the ampere-hour integration of online data [7]. In practical applications, there is a current drop at the charging end, and there are few high-quality charging segments that are completely “empty - fully charged”. The calculation results of the same vehicle fluctuate greatly each time, and SOH is difficult to determine and predict.

3.3 Analysis of Internal Short Circuit

During the actual use of power batteries, some batteries with poor manufacturing processes may have relatively obvious minor internal short circuits. The slow discharge of the battery leads to the outlier of individual cells. The outlier of cells will also accelerate the aging of the battery during use, reduce the reliability of the system, and increase the risk of thermal runaway. Therefore, detecting outlier cells, charging and balancing those with a high degree of outlier, and replacing the battery packs are important methods to enhance battery safety. The internal short circuit detection algorithm is mainly based on online data to obtain the characteristic value data of battery cells through eigenvalue algorithms such as Shannon entropy (Improved Shannon entropy) [8] and Z-value normalization, and then to obtain abnormal battery cells through clustering algorithms. Common clustering algorithms include DBSCAN, K-means, etc. Some scholars have also achieved short-circuit fault diagnosis within battery packs by enhancing the Conformer-Bi GRU network through convolution [9].

3.4 Lithium Plating Analysis

Early lithium plating detection requires disassembling the battery, which is irreversible and difficult to implement in real vehicle batteries. Non-destructive testing technology has developed rapidly. The impedance method determines the degree of lithium plating based on changes in battery impedance, but it is not sensitive to early lithium plating. After being fully charged, batteries with a higher degree of lithium plating will have a greater degree of self-discharge than other batteries. The relaxation voltage method developed based on this feature has good applications in practice, but users still need to let the vehicle rest for a period of time after charging is completed [10].

3.5 Battery Model Analysis

The battery system is characterized by complexity, time-varying nature, and nonlinearity. Some scholars predict the battery state by modeling it and issue early warnings by comparing it with the actual state. The current models are mainly divided into: equivalent circuit models and electrochemical models.

The equivalent circuit model refers to a model that describes the characteristics of a battery by forming a circuit network with electrical components. The commonly used equivalent circuit models are the first-order and second-order RC models. The laboratory simulation accuracy is relatively high, but in actual working conditions, the voltage and current data are out of sync and the accuracy is relatively low, which limits their application.

The electrochemical model is a comprehensive characterization of the electrochemical reactions during the charging and discharging process of batteries based on the principles of battery chemistry, with relatively high precision. The pseudo-two-dimensional model (P2D) is one of the basic models, but the P2D model is rather complex, involving numerous parameters, with a complicated calculation process and a long time consumption, which is not conducive to practical application.

3.6 Electrochemical Impedance Spectroscopy

Electrochemical impedance spectroscopy (EIS) technology can reflect the physical and chemical characteristics inside batteries, which is helpful for constructing equivalent circuit models, detecting aging states, and identifying abnormal cells. Traditional EIS rely on electrochemical workstations, which are large in size, unable to detect in real time, and cannot be deployed to battery cells [11]. Vehicle-mounted EIS deploys micro-sampling chips on individual battery cell acquisition boards, which can complete EIS detection under all working conditions with relatively low accuracy loss. There are already relatively mature hardware solutions with low costs, and it will have a relatively large application prospect [12]. The principle of the EIS system is shown in Figure 4, which visually presents the hardware composition of the on-board EIS detection system and the differential communication mechanism between the battery module and the main control board.

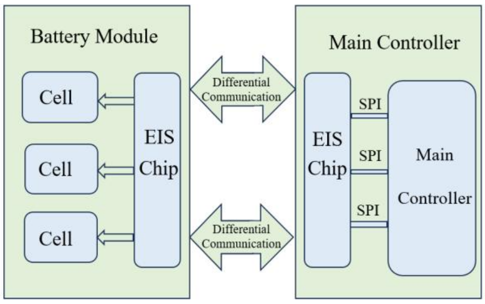

Figure 4. Operating Principle of the EIS System

3.7 Data-driven Model

Data-driven models refer to nonlinear battery models constructed through machine learning and deep learning. In recent years, related research and applications have been quite extensive, such as support vector machines [13], convolutional neural networks (CNNS), and long Short-Term recurrent neural networks (LSTM) [14], which can accurately estimate and predict features such as battery SOC, SOH, voltage, and temperature. And safety early warning and health management of lithium batteries.

However, data-driven training requires a considerable amount of real vehicle data with obvious fault features, but the actual vehicle's fault data is scarce. The scarcity and imbalance of faults also increase the difficulty of model training.

4. Safety Early Warning System Architecture

According to national standards, vehicles are generally equipped with a “Terminal-edge-cloud architecture”, namely BMS, edge-side intelligent terminals, and cloud platforms. The BMS performs functions such as data acquisition, status judgment, and battery control. Intelligent terminals temporarily store and upload battery paradigm data. The cloud platform conducts full life-cycle data storage, data push and display.

The overall architecture of the “Terminal-edge-cloud” battery safety early warning system is shown in Figure5, which demonstrates the division of labor and interaction relationship among BMS, edge intelligent terminals and cloud platforms in the closed loop of data collection, transmission and early warning.

The "Terminal-edge-cloud" battery safety early warning system developed based on this architecture deploys threshold alarm on the BMS side. At the initial stage of a fault, it cuts off high-voltage equipment, controls the operation of fire-fighting equipment, and promptly alarms through instrument panels, etc. Threshold alarm generally only alarms for "value-rate" and cannot make effective predictions. Intelligent terminals have a certain computing power. By deploying simple computing models and mining early fault characteristic signals, the timeliness of early warning can be improved. It can also be used in conjunction with BMS to achieve high-frequency storage of specific signals triggered by events. The model for the deployment of intelligent terminals is relatively simple, with generally low calculation accuracy and short early warning time. The cloud platform has high computing power, traffic and capacity. It can perform complex model calculations on all vehicles equipped on the platform, which is conducive to achieving daily and monthly early warnings. After the early warning information is reviewed, it will be alarmed through the alarm module configured on the platform via text messages, phone calls, etc.

The closed loop of safety early warning is also an important task. After the alarm is pushed, the after-sales personnel will detect and repair the battery status and feed back the detection results. Then, the algorithm will be optimized to gradually improve the accuracy of the algorithm.

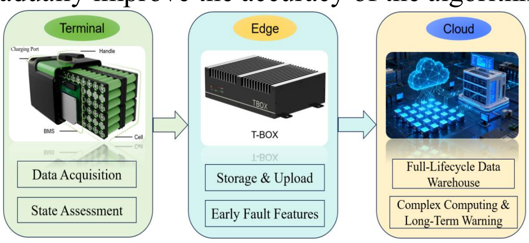

Figure 5. Early Warning Architecture Based on the "Terminal–Edge–Cloud" Collaboration

5. Problems and Challenges

Research on battery safety early warning has achieved certain results, but it also faces some problems and challenges, mainly including: low coupling degree between characteristic parameters and safety, few detection dimensions, few ideal data fragments, and low data quality.

5.1 Characteristic Parameters & Safety Risks: Low Coupling

When it comes to battery safety warnings, inferring battery failure based on the early minor characteristic changes of the battery is mostly a probabilistic sign. That is, if such parameters are abnormal, it indicates that the battery has a relatively high probability of safety hazards. Based on this, potential safety hazards of the battery can be dealt with in advance. However, battery aging does not necessarily mean that the battery will have safety problems. Even for some batteries, there is basically no change in characteristic parameters before failure, and the failure is sudden, which is called sudden death thermal runaway. These have brought difficulties to battery early warning.

5.2 Few Detection Dimensions

The battery is a complex black box system. Based on cost and operability, the current monitoring mainly focuses on data such as battery temperature, voltage, and current. According to the principle that information does not multiply, no matter whether data statistics, machine learning, or other means are adopted, the total amount of information will not increase, which means that the safety information available is limited. To improve the accuracy and advance nature of battery safety early warning, there must be a sufficient number of battery parameters as a basis, so more detection methods and dimensions are needed.

5.3 Limited Ideal Data Fragments

The actual operating conditions of batteries are different from the ideal conditions in the laboratory, and the application of some detection methods is to some extent limited. For instance, in the case of lithium plating detection, in actual use, it is relatively rare for a battery to remain static after being fully charged and not discharged. For this purpose, it is necessary to modify the power-on and power-off logic, add a 24-hour monitoring function, and at the same time enhance the ability to capture feature fragments.

5.4 Low Data Quality

During the process of data collection and transmission, problems such as data asynchrony, noise, duplication and loss may occur. Duplicate and missing data can generally be resolved through deduplication and supplementation. The superimposition of data asynchronization and noise can have a significant impact on the results of safety warnings, especially when the discharge condition is superimposed with kinetic energy recovery. The same frame of data may be in the discharge and kinetic energy recovery charging conditions respectively, resulting in a large difference between the data. In addition, the data retention period stipulated by the national standard is 10 seconds, which makes it easy to lose key information under rapid changes.

6. Summary and Outlook

Battery safety early warning is one of the important means to enhance the safety of power batteries. Starting from the battery mechanism, it studies the characteristics of battery degradation and loss of control. By constructing equivalent circuit models, electrochemical models, data-driven models and other models to analyze battery data, it can identify abnormal battery cells to a certain extent and issue early warnings for handling. Currently, safety early warning technology has been widely deployed and applied.

The existing methods also have some problems. Issues such as low coupling between feature parameters and security, few detection dimensions, few ideal data fragments, and low data quality restrict the development of security early warning. In recent years, a number of new technologies have been emerging one after another. The actual vehicle deployment of new types of sensors, such as pressure and gas sensors, can expand the dimension of characteristic parameters and bring more possibilities for safety early warning. The battery large model integrating battery mechanism has a large parameter scale, stronger learning and expression capabilities, and features strong capabilities in processing complex data and generalization, multi-modal fusion, and wide coverage of failure modes. These technologies are gradually enhancing the accuracy and timeliness of safety warnings. Along with the advancement of materials and processes, they jointly improve the safety of batteries, reduce hazards and losses, and promote the development of the new energy vehicle industry.

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