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Beyond Limits: A Brief Exploration of Fault Detection and Balancing in Lithium-ion Battery Technology

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Abstract. The process of achieving balance among sequentially connected cells is crucial to prevent excessive charging or discharging, and it also improves the overall energy capacity. This article discusses various algorithms created for equalizing cell charge within a battery management system (BMS). Proper cell balancing is indispensable for upkeeping lithium-ion battery (LiB) packs. Within the BMS, identifying faults is of utmost importance. This encompasses detecting, isolating, and estimating faults. To prevent batteries from operating in unsafe ranges, it is vital to ensure the accurate functioning of current, voltage, and temperature sensors. Accurate fault diagnosis is pivotal for the optimal operation of battery management systems. In the context of electric vehicle battery management systems, precise measurement of current, voltage, and temperature is greatly relied upon to estimate the State of Charge (SOC) and overall battery health. Swiftly identifying early failures can mitigate safety hazards and minimize damage. Nevertheless, effectively pinpointing these initial failures using genuine operational data from electric vehicles remains a intricate task. This paper presents an analysis of different algorithms for detecting balancing-related faults, covering both methods based on models and those not reliant on models. The strengths and weaknesses of the evaluated algorithms, along with upcoming challenges in the realm of balancing and fault detection for LiBs, are also discussed in this document.

1. Introduction

LiBs find extensive application in new energy vehicles (NEV) due to their crucial role as substantial energy storage systems (ESS). For effectively managing and controlling such a vast number of cells, a precise and versatile battery management system (BMS) is absolutely essential. Within electric vehicles (EVs), LiB packs hold immense significance as a foundational element. These packs are composed of numerous cells interconnected using series and parallel setups to provide the necessary power and energy for the vehicle's operation.

In order to improve the effectiveness of techniques for diagnosing battery faults, Wang et al. [1] introduced a method for detecting faults in LiBs utilized within electric vehicles. This approach integrates multiple data-driven strategies to achieve a comprehensive analysis. Initially, deviations are eliminated, and initial fault assessments are conducted using a combination of t-distribution random neighborhood embedding (t-Sne) and wavelet transform denoising. Subsequently, significant vehicular attributes that have a notable impact on battery faults are identified through factor analysis. These critical attributes that lead to faults are then extracted using a combination of a two-way long and short-term memory network and a convolutional neural network. Finally, a self-learning Bayesian network is deployed to recognize and diagnose battery faults. Experimental results indicate that this method enhances the accuracy of fault diagnosis by approximately 12% when validated with various vehicle data. When compared to other approaches, this method not only achieves higher precision in fault diagnosis but also reduces the time required for fault identification. Furthermore, its performance surpasses that of graded fault systems, making it more closely aligned with real-world engineering applications [1].

Cai et al. [2] have introduced a multi-fault detection approach for battery packs connected in series. This technique incorporates elements of Attentional Mechanisms and Domain Adaptation Neural Networks, enabling the detection of various types of faults (specifically, voltage imbalance, internal short circuit, sensor anomalies, sensor drift voltage, and random fluctuation). By combining the advantages of both Attentional Mechanisms and Domain Adaptation Neural Networks, this innovative method, referred to as the Category-Reinforced Domain Adaptation Network, demonstrates effectiveness. It possesses the ability to diagnose multiple types of faults within battery packs. Through validation on a real-world platform encompassing three distinct operational scenarios, the approach showcases its capability. It enhances the model's ability to adapt across various battery pack contexts and notably contributes to the successful identification of multiple faults within battery packs [2].

Kosuru et al. [3] put forth a comprehensive framework for battery data analysis, with a specific focus on LiBs. This framework harnesses deep learning to detect and classify faulty battery sensor readings and transmission information. The study commences with the collection of sensor data, followed by preprocessing that involves z-score normalization. Subsequently, feature extraction is conducted using sparse principal component analysis (SPCA), while feature selection is facilitated through the enhanced marine predators algorithm (EMPA). A novel approach called the Incipient Bat-Optimized Deep Residual Network (IB-DRN) is introduced to enhance the safety and reliability of the BMS. This approach forms the foundation for identifying and categorizing erroneous battery data. The research employs MATLAB along with a combination of statistical analysis, machine learning techniques, and a deep learning toolbox. Experimental investigations are also conducted to demonstrate and evaluate the effectiveness of the proposed strategy. The results indicate that the suggested methodology surpasses conventional techniques, exhibiting superiority across various aspects.

Liu et al. [4] presented a solution in the form of a toggleable indicator designed to enhance the balancing of a battery pack connected in series. This is achieved by integrating a bypass equalizer with distinctive attributes including a compact topological structure, high efficiency, and intrinsic fault tolerance capabilities. The proposed toggleable indicator allows for the automatic selection of balance indicators, enabling a smooth transition between voltage and SOC based indicators. This inventive approach sets the stage for the development of a new balancing strategy that makes optimal use of the capabilities of the toggleable indicator. To validate the effectiveness of this approach, the proposed method undergoes both simulation and experimental testing using a LiB pack [4].

Fan et al. [5] introduced an MPC approach with rapid balancing to tackle inconsistency in LiB packs, optimizing energy transfer and minimizing SOC differences. Their MPC-based equalization algorithm aimed to efficiently reduce SOC variations, complemented by a quick-solving strategy to enhance computational efficiency. The method showcased superior performance in achieving swift equalization and minimizing energy wastage, with a key highlight being the avoidance of unnecessary battery cycling. This approach not only improved balancing accuracy but also demonstrated enhanced computational effectiveness compared to conventional techniques.

2. Balancing of LiBs

Figure 1 demonstrates an instance of battery cells being unbalanced. Several possible arrangements have been suggested to achieve balance in a battery bank, as described in various proposals [6]. All of these arrangements adhere to three fundamental methods, as shown in Figure 2. The first method involves discharging excess energy from battery cells. The next approach revolves around redistributing energy from cells with higher charge levels to those with lower charge levels. The last strategy involves controlling the charging or discharging current of each cell to ensure consistent SOC levels across all cells [7].

Figure 1. Unbalanced battery cells.

A highly reliable and efficient BMS is of great significance for applications powered by electrochemistry. Among the crucial features of a BMS, the aspect of cell balancing emerges as paramount. The purpose of cell balancing techniques is to ensure a fair distribution of energy among battery cells. The absence of proper cell balancing would lead to the wastage of capacity or energy within the battery array, a concern that becomes more pronounced in extended battery strings subject to frequent charge-discharge cycles. Qi et al. [7] categorizes several well-established cell balancing methods, organizing them based on their approach to managing excess energy within battery cells [7].

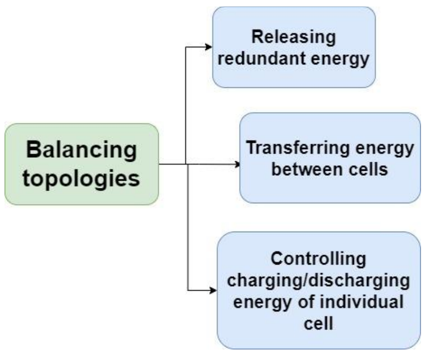

Figure 2. Cell Balancing Topologies Category [7].

Piao et al. [8] utilized a distance-based outlier detection method that relies on two main parameters—voltage and SOC—to calculate unusual values for individual cells. This enables the detection of unbalanced cells. By means of an online clustering approach, the algorithm differentiates between battery cells that are normal and those that are abnormal. To address the imbalance, bleeding circuits were applied to the cells identified as abnormal. The simulation results illustrate that the proposed balancing algorithm significantly improves the usable capacity of the battery pack, achieving a notable 9.5% increase compared to situations where balancing was not implemented [8].

Chowdhury and colleagues [9] introduced a novel strategy to achieve equilibrium in the State of Health (SOH) among interconnected LiB cells using DC/DC converters. SOH has become a significant gauge of battery health, alongside SOC, internal resistance, and conventional metrics. The adjustment of SOH balance is crucial for effectively utilizing battery cells that have varying capacity characteristics due to aging. They presented a simplified configuration to balance SOH in LiB cells linked via DC/DC converters, providing power to a shared load. Their uncomplicated approach was especially fitting for situations with limited battery maintenance access. The adoption of the proposed SOH balancing technique had the potential to elongate the overall operational lifespan of the battery storage unit and curtail replacement expenses.

Bonfiglio and colleagues [10] presented an active method for equalizing cells within stacks of LiBs. It is a widespread practice to balance the charge of individual cells in multi-cell LiB stacks to prevent harm and improve battery longevity. At present, the majority of battery stacks utilize a passive cell balancing approach that dissipates charge as heat through a resistor. In contrast, their approach utilizes a flyback converter to transfer charge between cells, leading to minimal energy wastage and a slight increase in cost compared to conventional passive systems.

McCurlie and his colleagues [11] introduced an advanced continuous-time fast model predictive control (MPC) method. This approach utilizes performance measures to establish an equilibrium in the SOC among battery pack components. Simulation outcomes illustrate that the MPC strategy achieves singular-point convergence of SOC, surpassing the performance of a traditional rule-based algorithm. This development enhances the efficiency of power electronics and extends the operational lifespan of battery cells by reducing frequent transitions between cell charging and discharging. Experimental results highlight a redistributive battery balancing system that rapidly accomplishes equilibrium by combining fast MPC with readily available microcontrollers found in today's market.

Zhang and co-authors [12] introduced a dynamic method for actively balancing the charging and discharging of LiB packs based on the average SOC. Two distinct active balancing strategies were developed to manage the varied charging and discharging conditions of the LiB pack. For charging, a balancing strategy was implemented that focuses on cells with SOC higher than the average SOC of the LiB pack, thereby enhancing the overall charging capacity. Conversely, during discharging or periods of rest, a different balancing strategy was employed, targeting cells with SOC lower than the average SOC of the LiB pack, thus improving the overall discharging capacity. Experimental findings confirm the effectiveness of this proposed active balancing approach. It showcases a reduction in energy discrepancies among battery cells and an improvement in both the charging and discharging capabilities of the LiB pack.

In contrast to prior studies, the maximum allowable current for cell equalization is adjusted to vary in accordance with changes in the external current of the battery pack. Ouyang and colleagues [13] aimed to prevent cell currents from surpassing their predetermined limits, as opposed to using a constant maximum value. By employing adaptive quasi-sliding mode observers to accurately SOC, they introduced a discrete-time quasi-sliding-mode-based strategy that integrates limited equalization currents. This strategy coordinates the collaborative operation of converters to efficiently achieve SOC equalization among cells. Through mathematical analysis and supported by experimental results, they demonstrated that the actual SOC discrepancies among cells can swiftly converge within an acceptable range centered around the origin.

To thoroughly investigate the influence of load cycles in conjunction with different BMS, Ziegler and co-authors [14] conducted a comprehensive assessment of individual cells. The findings of the study indicate that active balancing leads to a maximum improvement of 2% in usable capacity compared to passive balancing. Furthermore, active balancing alleviates inconsistencies among cells in terms of capacity and internal resistance. Notably, the study demonstrated that the additional stress caused by frequent energy redistribution in active balancing systems does not result in detrimental aging effects on cells when compared to passive balancing approaches.

Räber and collaborators [15] provided a theoretical examination that details an approach for evaluating the benefits of cell-to-cell active charge balancing circuits compared to passive balancing alternatives, with a specific focus on energy preservation and capacity improvement. The assessment involves the utilization of variable parameters, including battery system configuration and distribution characteristics of cell capacity. Their study computed the inefficiencies linked to passive balancing within a battery system, while also approximating the overall energy conservation achievable through the use of cell-to-cell active balancing. The increase in capacity of a battery system utilizing active balancing, relative to a passive equivalent, was determined to fall in the range of 1.06 to 1.01.

Hua et al. [16] aimed to present a reliable and accurate method for assessing the SOC and SOH of battery packs that consist of multiple cells linked in a series configuration, utilizing passive balance control. In the initial stages of their research, the authors introduced the notions of individual cell-level and overall pack-level states. They provided clear explanations of how the conditions of individual battery cells are interconnected with the overall state of the battery pack. Subsequently, they formulated a multi time-scale approach to predict the SOC/SOH of the battery pack. Within this framework, the evaluation of SOH (which relates to gradual changes) is conducted over extended time periods, while SOC (which involves rapid changes) is estimated in real-time. To put their approach into practice, they adopted a non-linear predictive filter (NPF) as the estimation algorithm, which significantly enhanced the accuracy of SOC and SOH assessments. To validate their findings, the researchers performed experiments using a battery pack under specific driving cycles, confirming the effectiveness of the proposed methodology. The experimental results underscore the capability of the methodology to precisely gauge both the SOC and SOH of the battery pack.

3. Fault diagnostic of LiBs

The causes of battery deterioration at the anode and their consequences are depicted in Figure 3. Wu et al. [17] provided a comprehensive overview of the most recent research and progress in comprehending the mechanisms behind the aging of LiBs. By gaining insights into the origins and indications of battery malfunctions, this review encompasses the predominant factors that contribute to aging, along with the corresponding effects and results. Through the implementation of aging tests, the intricate relationship between performance and aging components, as well as their interconnected consequences, can be accurately gauged. The article concludes by summarizing recent advancements in diagnostic technologies for detecting battery malfunctions, accompanied by a fair assessment of their pros and cons. Ultimately, the paper proposes innovative strategies for diagnosing faults and outlines the enduring challenges that persist in this field [17].

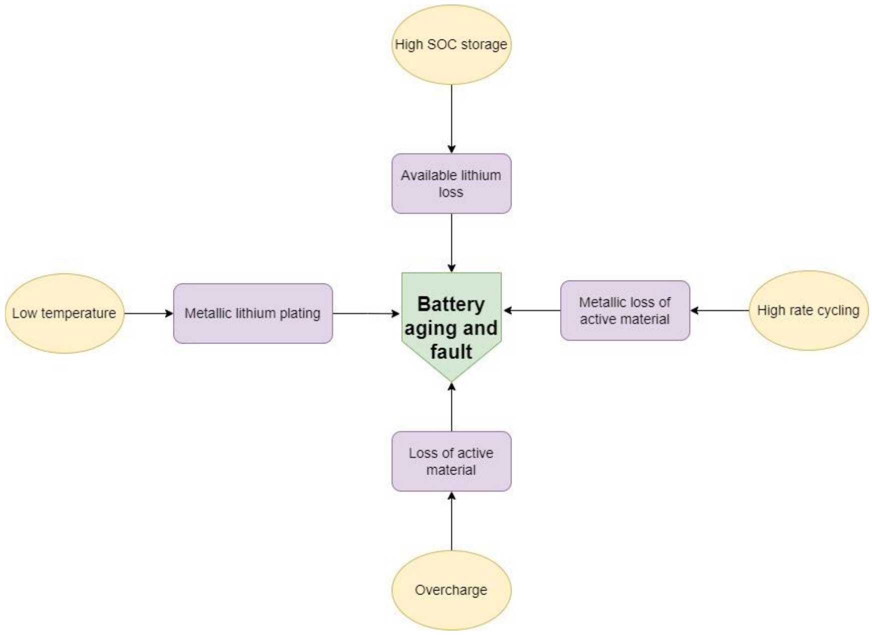

Figure 3. Causes for battery ageing at anode and their effects [17].

A basic diagram illustrating the algorithm used for identifying faults via state estimation is presented in Figure 4. Diverse categories of battery models are accessible, including those related to electrochemical, electrical, thermal aspects, and interdisciplinary variations such as electro-thermal combinations [18]. Figure 5 demonstrates transformations in a diagnostic system. The selection of a model for aiding in fault detection relies on the specific requirements of the LiB application. Model-based approaches are commonly preferred for fault detection due to their simplicity and cost-effectiveness. These approaches encompass techniques like state estimation, parameter estimation, parity equations, and structural analysis [20]. The categorization of diagnostic algorithms for identifying faults in LiBs is depicted in Figure 6. Diverse industries utilize a range of approaches for diagnosing faults. Yet, concerning LiB applications, the presence of both internal and interconnected faults often renders many conventional techniques from other domains inapplicable. Within the scope of LiBs, methods for diagnosing faults can be divided into two main groups: those that utilize models and those that don't rely on models [19]. This section will showcase recent progress in the realm of fault diagnosis, addressing concerns related to both internal and external issues associated with LiBs. Broadly, the process of making diagnostic decisions can be conceptualized as a sequence of conversions or mappings applied to process measurements. Figure 5 illustrates the distinct transformations that process data undergo throughout the diagnostic process.

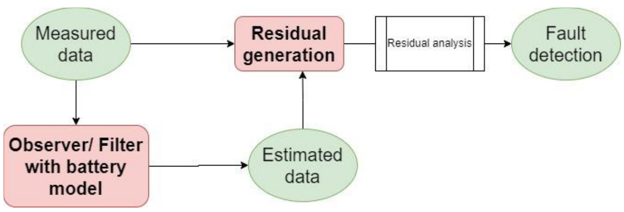

Figure 4. A simplified schematic of state estimation fault diagnosis [20].

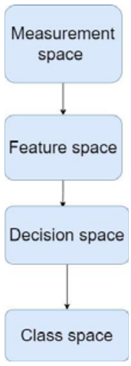

Figure 5. Transformations in a diagnostic system [19].

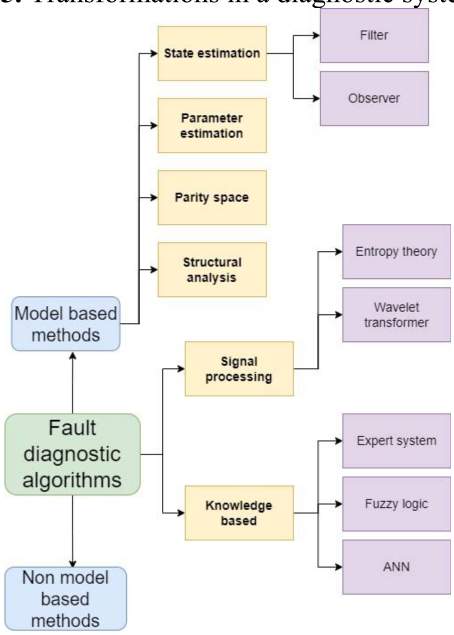

Figure 6. The classification of LiB fault diagnostic algorithms [20].

Xiong et al. [21] introduced a direct and efficient model-based strategy for detecting faults in sensors. Their method was specifically tailored to detect and isolate malfunctions in current or voltage sensors within an interconnected LiB pack. To differentiate between faults in sensors and faults in battery cells, a temperature sensor (assuming its proper operation) is utilized. This allows for distinguishing between a malfunction in a current or voltage sensor and a fault in a battery cell. Consequently, defective current or voltage sensors can be recognized by comparing the residual values of each cell with a predetermined threshold. The effectiveness of this proposed approach for diagnosing sensor faults is verified through both experimental tests and simulations, affirming its practical viability.

Zheng et al. [22] introduced an innovative technique to identify faults in voltage and current sensors within a LiB pack system. This approach integrates hybrid system modeling with the unscented particle filter, providing an efficient solution to this significant issue. By conducting experiments on a battery pack with a serial-parallel configuration, different fault scenarios concerning voltage and current sensors were evaluated. The results showcase that the method proposed in this study excels not only in precisely monitoring the system's state but also in accurately diagnosing faults within the sensors of the LiB system.

To extract insights related to faults from real-world electric vehicle usage data, Fan et al. [23] introduced an innovative approach involving the development of a generalized dimensionless indicator (GDI) along with a tolerance factor. The GDI is carefully crafted for the purpose of this study. By plotting these dimensionless indicators on a two-dimensional plane, the evolving patterns of voltage anomalies are visually displayed. To distinguish the changing anomaly patterns, the Local Outlier Factor (LOF) algorithm is utilized. This algorithm assists in recognizing the progression of anomalies, isolating malfunctioning batteries, and pinpointing the exact time of a fault occurrence. To mitigate the influence of cell variations on diagnostic accuracy, a differential technique is implemented. The effectiveness of the proposed method is validated through experiments conducted using real-world vehicle data. The results of the experiments emphasize the method's capability to effectively detect early-stage battery failures, showcasing both precision in fault identification and overall robustness.

Ma et al. [24] introduced an innovative dual-Kalman filter diagnostic method through a comprehensive analysis of the features of external soft-short circuit faults in series-connected LiB packs. The experiments were carried out for two main objectives: to understand the nature of the fault and to validate the effectiveness of the diagnostic algorithm. The suggested diagnostic technique exhibits remarkable capability in identifying external soft-short circuit faults, thereby highlighting its potential for precise fault detection and diagnosis.

Qiu et al. [25] utilized the local outlier factor (LOF) technique to conduct fault diagnosis on energy storage systems relying on LIB ESSs. The authors proposed two distinct algorithms for input generation within the LOF method: the multiple factors at a single time step input generation (MFST) algorithm and the single factor at multiple time steps input generation (SFMT) algorithm. To model various degrees of internal short circuit (ISC) severity, an ISC model was integrated into an electrical-thermal coupled model for an air-cooled LIB ESS. The performance of the LOF method was evaluated in detecting different levels of ISC severity, with assessments based on simulated data from the air-cooled LIB ESS and experimental data from a water-cooled LIB ESS.

Zhang et al. [26] presented a novel online multifault diagnosis approach that combines model-based and entropy methods to effectively detect and isolate various types of faults. These encompass faults in current, voltage, and temperature sensors, along with short-circuit faults and connection faults. To distinguish voltage sensor faults from battery short-circuits or connection faults, an interleaved voltage measurement topology is implemented. Leveraging a comprehensive battery model, structural analysis is employed to design diagnostic tests tailored to different fault categories. The extended Kalman filter is used for residual generation, followed by statistical inference for residual assessment, enabling the identification and isolation of sensor faults. Subsequently, sample entropy is employed to further differentiate between short-circuit faults and connection faults. The efficacy of the proposed diagnostic approach is validated through multiple fault tests involving various fault types and magnitudes. Importantly, the results highlight the method's resilience in managing noise and discrepancies in SOC and temperature data.

Lin et al. [27] introduced a comprehensive fault diagnostic strategy grounded in hybrid system theory, specifically designed to address common issues in LiB packs, including sensor and relay faults. This method utilizes automata, constructed on the principles of hybrid systems, to effectively incorporate the continuous and discrete dynamics inherent in battery packs. To manage computational complexity, a distributed diagnostic structure is employed, eliminating the necessity for a global battery pack model. The core of the approach lies in a dual extended Kalman filter algorithm, facilitating the estimation of crucial parameters like terminal voltages and SOC for individual battery cells within the pack. Residuals from current, terminal voltage, and SOC serve as foundational components for executing distinguishability analysis, which aids in identifying faults. The diagnostic process combines event observation with distinguishability analysis based on continuous dynamics. The efficacy of this diagnostic approach is verified through validation on a battery pack configuration comprising two series-connected batteries and two parallel-connected branches. Validation is conducted using the Federal Urban Driving Schedule driving cycle, affirming the robustness and practicality of the proposed method.

Xiong et al. [28] focused on online fault diagnosis specifically targeting External Short Circuits (ESC) in LiB packs. They conducted experimental investigations to gather and compare ESC characteristics between an NMC battery pack and a single cell. Utilizing the insights from experimental analysis, they formulated a two-step equivalent circuit model to describe the ESC process. An online model-based approach was then developed for diagnosing ESC faults within battery packs. The effectiveness of this approach was evaluated using experimental data. The results showcase its capability to precisely diagnose ESC faults within 3.5 seconds of occurrence, with a terminal voltage error of under 25 mV. Notably, the proposed method demonstrates robust generalization capabilities, successfully diagnosing ESC faults in battery packs with varying numbers of cells connected in series and in scenarios where current information is unavailable. In these cases, the terminal voltage error remains below 48 mV and 60 mV, respectively.

Jiang et al. [29] introduced a fault diagnosis technique for power LiBs, utilizing the isolated forest algorithm. The approach involves several key stages. Initially, the original voltage data undergo signal processing and decomposition, separating the data into static components, which exhibit strong correlations with aging inconsistencies, and dynamic components, which capture abnormal patterns. Subsequently, characteristic parameters are extracted from these static and dynamic components. These parameters are then fed into the isolated forest algorithm, which performs anomaly detection to identify cells with abnormalities. The proposed method was extensively tested using voltage data from four vehicles with defective batteries. The results of these tests confirm the method's ability to effectively detect both gradual and sudden failures. This validates its suitability for diagnosing power LiB faults and underscores its potential for real-time implementation in actual vehicles.

Shang et al. [30] introduced a real-time multi-fault diagnosis technique designed to detect early battery failures, utilizing a modified Sample Entropy approach. By analyzing the modified Sample Entropy of cell-voltage sequences within a moving window, the method effectively identifies and predicts various early battery faults, including short-circuit and open-circuit faults. Additionally, it can estimate the timing of fault occurrences. Experimental results, along with comparisons against traditional methods, validate the effectiveness of this proposed approach. It showcases robustness, reliability, and computational efficiency, all while bypassing the necessity for an exact model. In summary, this multi-fault diagnosis strategy demonstrates feasibility and potential in real-world electric vehicle applications, addressing the intricate nature of LiBs and offering early detection and prediction of faults.

Li et al. [31] introduced an inventive fault detection method that merges Empirical Mode Decomposition (EMD) with Sample Entropy (SE) to adeptly identify battery faults across diverse operating conditions. The proposed approach initiates by extracting relevant fault features using the EMD technique. This involves decomposing battery voltage signals and mitigating noise interference during voltage sampling. Through experimentation, the significance of fault features extracted by EMD is quantified. Subsequently, utilizing these extracted fault features, Sample Entropy values are computed. These values contribute to accurate fault detection and localization. Furthermore, a framework for evaluating the detected faults is devised to indicate the severity of battery faults. The efficacy of the method is then established using real-world data collected from electric vehicles, spanning scenarios involving routine and abrupt faults. This validation underscores the effectiveness of the proposed methodology in precisely detecting and diagnosing battery faults within varying operational contexts.

4. Challenges in Fault Detection and Balancing

Advancements in LiB fault detection include sophisticated BMS, integrating data analytics and machine learning for accurate fault prediction, enhanced sensor technologies, efficient thermal management systems, redundancy and diagnostics, and continuous condition monitoring. However, challenges persist in addressing complex failure modes, integrating advanced technologies seamlessly, balancing cost-effectiveness, ensuring data security, achieving scalability, and considering the full lifecycle of batteries. Overcoming these challenges requires collaborative efforts to develop standardized and cost-effective solutions, emphasizing ongoing research and development to ensure the safe and reliable use of lithium-ion battery technology across various applications.

Identifying issues and maintaining equilibrium are crucial aspects of effectively managing LiBs to ensure their safety, efficiency, and longevity. These batteries are widely used in various applications, from portable electronics to electric vehicles, and are susceptible to developing defects or inconsistencies over time that can compromise their performance and safety [32].

Here is a summary of fault detection and balancing in the context of LiBs:

Fault Detection: Detecting malfunctions in LiBs involves monitoring various parameters and characteristics to identify abnormal behavior [33]. Common malfunctions include excessive charging, extreme discharging, thermal escalation, capacity deterioration, and internal short circuits. Approaches to fault diagnosis include: Continuous Voltage and Current Monitoring: Persistent tracking of voltage and current during charging and discharging can reveal irregularities, such as abrupt spikes or plunges in voltage indicating problems [34].

Temperature Monitoring: Temperature sensors within the battery assembly can identify instances of overheating, a critical safety hazard [35].

Impedance Spectroscopy: Measuring the battery's impedance at different frequencies provides insights into changes in its internal structure and state [36].

Voltage Hysteresis: Monitoring voltage hysteresis during charge and discharge cycles can uncover capacity reductions or discrepancies [37].

SOC and SOH Estimation: Advanced algorithms can estimate the battery's SOC and SOH based on various parameters, helping discern deviations from normal behavior [38].

Balancing: Cell balancing involves equalizing the charge and discharge capacities of individual cells within a battery assembly [39]. Due to variations in production and operation, cells may have different capacities and voltage levels, leading to imbalances. Balancing is essential for maintaining consistent cell performance and extending the overall lifespan of the assembly. Various balancing strategies exist:

Passive Balancing: This strategy uses resistors or bleed circuits to disperse excessive charge from cells with higher voltages. It is simple but may be inefficient and generate heat [40].

Active Balancing: Active balancing incorporates additional circuitry to redistribute charge across cells, proving more effective and reducing heat production [41].

Cell Transfer Balancing: Physically transferring charge between cells is an alternative method, although less common due to its complexity [42].

Voltage Threshold Balancing: Balancing activates when a cell's voltage exceeds a specific threshold. This approach is efficient but requires monitoring circuitry for each cell [43].

Energy Transfer Balancing: Energy is transferred between cells using capacitors or inductors, proving more efficient and faster than some other methods [44].

To implement these techniques proficiently, battery management systems (BMS) play a crucial role [45]. A BMS oversees and regulates the battery's charging, discharging, and balancing processes. It collects data from individual cells and controls charging and discharging rates to prevent faults and imbalances.

Figure 7 illustrates the design of the Battery Management System (BMS) along with certain limitations. A significant challenge associated with the offline BMS is the inconsistency of state estimation algorithms [47]. Additionally, a notable drawback in the existing BMS is the absence of dependable real-time fault diagnosis algorithms [48]. Various battery faults encompass sensor malfunctions, cell connection issues, internal short circuits, external short circuits, overheating, and thermal runaway [49].

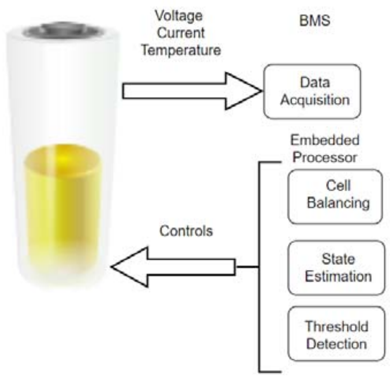

Figure 7. Battery management system design and functions [46].

5. Discussion

5.1 Introduction to LiBs and Challenges

LiBs have garnered increased attention as a dependable energy storage solution with extended operational lifespan and improved energy and power density. However, the natural aging of batteries leads to performance decline and potential system malfunctions, posing risks such as thermal runaway or explosions. Challenges arise from diverse production and operational conditions of connected cells, making it challenging for the BMS to ensure the safe operation of each cell.

5.2 Battery Balancing and Variability

Energy storage systems employing LiBs require cell balancing due to inherent manufacturing differences, varying self-discharge rates, disparities in internal resistances, and temperature variations among cells. Inconsistencies in LiB cell conditions can result in uneven residual capacity, risking cell damage due to overcharging or overdischarging.

5.3 Fault Diagnosis and Safety

Ensuring the safety and reliability of advanced battery management systems is a complex challenge, especially in diagnosing external soft-short circuit faults. Safety is paramount for LiBs, considering the potential for fire accidents under faulty conditions. Fault diagnosis involves detecting abusive conditions and identifying faulty batteries early to prevent escalation into thermal runaway. The LiB system faces various faults compromising performance and safety, and traditional fault-diagnosis methods struggle to identify early-stage issues without clear abnormality signs.

5.4 Challenges in Battery Management and Fault Detection

Voltage signals during battery operation are susceptible to noise interference. In electric vehicles, even minor malfunctions in power batteries can lead to accidents. Progressing safely in electric vehicles depends on swiftly identifying and accurately differentiating battery pack faults. Identifying fault characteristics within LiB packs, which vary in types and health statuses, presents challenges.

5.5 Sensor Data and BMS Robustness

Gathering and transmitting battery sensor data are crucial for BMS. Inaccuracies in battery data, stemming from sensor issues, communication problems, or cyber intrusions, can jeopardize BMS integrity and applications like electric vehicles. Hence, evaluating the robustness of battery sensor and communication data within BMS is critical. Sensor data underpin all BMS operations, and effective detection of sensor faults is pivotal for ensuring battery system sustainability and security in electric vehicles.

5.6 Battery Pack Balancing and Uniformity

Maintaining balance in battery packs is vital for their BMS. Insufficient balance limits overall battery pack performance to the capability of the weakest cell. Although Battery SOC is valuable for achieving balance, SOC estimation accuracy is not guaranteed, introducing uncertainties hindering balance optimization. Preserving LiB pack uniformity is essential for extending battery lifespan, maximizing capacity utilization, and ensuring safe electric vehicle operation.

Addressing these challenges requires collaborative efforts from researchers, industry stakeholders, and regulatory bodies to develop robust and standardized solutions for fault detection and balancing in lithium-ion batteries. Continuous research and development will play a crucial role in overcoming these challenges, ensuring the safe and reliable use of lithium-ion battery technology across various applications.

6. Conclusion

The LiBs has gained increasing attention due to its potential as a dependable storage solution, with extended operational longevity and improved energy and power density. However, the battery's operation leads to inevitable aging, causing a decline in performance and potential system issues. These consequences not only bring inconvenience but also pose significant risks such as thermal runaway or even explosions. The Battery Management System (BMS) performs vital functions, including estimating battery state, equalizing cell voltages, managing thermal conditions, and diagnosing malfunctions. Challenges arise due to the diverse production and operational conditions of series and parallel-connected cells, making it difficult for the BMS to ensure the safe operation of each individual cell.

Energy storage systems utilizing LiBs require cell balancing due to inherent manufacturing variations, differing self-discharge rates, disparities in internal resistances, and temperature differences among individual cells. Variations in the conditions and parameters of LiB cells can lead to inconsistencies in remaining capacity among cells, potentially resulting in cell damage due to overcharging or overdischarging. Active charge balancing has gained recognition as an effective approach to create more energy-efficient and environmentally-friendly setups for LiBs.

Dealing with the variability among cells within battery packs for electric vehicles (EVs), accurately estimating the SOC and SOH of battery systems poses a significant challenge, especially within the computational limits of battery management systems. The reliable operation of electric vehicles heavily relies on the proper function of LiB packs. Early detection of potential failures in LiB packs is crucial to ensure the safe and reliable operation of these vehicles.

Ensuring the safety and reliability of advanced battery management systems is a complex challenge, especially in diagnosing external soft-short circuit faults. This specific issue remains intricate and unresolved. The safety of LIBs is of utmost importance, particularly due to the potential for fire accidents when they are faulty or operate under abnormal conditions. Ensuring the safety of LIBs is a critical requirement for their widespread use.

One method to achieve this is through fault diagnosis, involving the detection of abusive conditions and identification of faulty batteries at an early stage to prevent them from progressing to thermal runaway. The LiB system is vulnerable to various faults that can compromise its performance and safety. Detecting these early faults is difficult, and false alarms can occur due to similarities in fault characteristics. A dependable fault diagnostic method is essential to ensure battery system performance and safety.

Ensuring battery safety is crucial when using LiBs in all-climate electric vehicles. Issues like short circuits, overcharging, and overheating are prevalent. Incidents of electric vehicle safety stemming from LiB failures have become more frequent in recent years. Notably, voltage data from a malfunctioning battery often show abnormal patterns before a safety incident. These abnormal voltage changes are more pronounced in progressive failures, while sudden failures may involve subtler voltage shifts. Conventional fault-diagnosis methods struggle to identify battery faults early on when no obvious abnormalities are present. This challenge arises due to the complexity, nonlinearity, and time-varying nature of LiBs, compounded by inherent cell inconsistencies.

Fault detection is a critical aspect of LiB operation in electric vehicles. Voltage signals during battery system operation are susceptible to noise interference. Power batteries are central components in electric vehicles, and even minor malfunctions can lead to accidents. Therefore, ensuring accurate diagnosis of battery issues holds great importance.

Ensuring the intelligent advancement and safe operation of electric vehicles largely depends on swiftly identifying and accurately distinguishing various battery pack faults. However, pinpointing fault characteristics within LiB packs, which vary in battery types and health statuses, proves challenging. In this context, domain-adapted neural networks show promise.

Collecting and transmitting battery sensor data is of paramount importance in Battery Management Systems (BMS). Inaccuracies in battery data due to sensor malfunctions, communication errors, or even cyber intrusions can pose significant threats to both BMS integrity and applications dependent on BMS, such as electric vehicles. Thus, evaluating the resilience of battery sensor and communication data within BMS is a critical endeavor.

Sensor data underlie all BMS operations. Effectively detecting sensor faults is pivotal for ensuring the sustainability and security of battery systems in electric vehicles. Maintaining balance within a battery pack is crucial for its Battery Management System (BMS). When not adequately balanced, the overall performance of the battery pack is limited by its weakest cell. While Battery SOC is a useful indicator for achieving balance, the accuracy of SOC estimation is not always assured, introducing uncertainties that can hinder balance optimization. Maintaining uniformity in LiB packs is highly important to prolong battery lifespan, optimize capacity utilization, and ensure the safe operation of electric vehicles. In conclusion, fault detection and balancing are essential for ensuring the secure and optimal performance of LiBs. Regular monitoring, appropriate use of balancing techniques, and the application of advanced battery management systems all contribute to extending battery life and reducing safety hazards.

In conclusion, the widespread adoption of LiBs in energy storage and electric vehicles comes with challenges, particularly in ensuring safety and optimal performance. The Battery Management System (BMS) plays a crucial role in addressing issues such as cell balancing, fault detection, and accurate estimation of battery state. Challenges include the diverse conditions of connected cells, manufacturing variations, and the complexity of fault diagnosis. Active charge balancing and advanced fault diagnostic methods, including domain-adapted neural networks, show promise in enhancing energy efficiency and safety. Additionally, the resilience of battery sensor and communication data within BMS is vital. Overall, continuous advancements in monitoring, balancing techniques, and BMS applications are essential for extending battery life and reducing safety hazards in the dynamic landscape of LiB technology, particularly in electric vehicles.

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