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Bridging battery degradation and safety: Challenges and opportunities

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ABSTRACT

As lithium-ion batteries continue to empower the global shift toward transportation electrification and renewable energy integration, ensuring their reliable, long-term and safe operation has emerged as a topmost challenge. Despite extensive research on both degradation mechanisms and catastrophic failures such as thermal runaway, these phenomena are often investigated in isolation, hindering the development of comprehensive safety strategies. This review bridges the critical gap between battery degradation and safety by establishing a unified framework that connects gradual degradation processes, fault evolution and extreme risks. We systematically examine how electrochemical degradation influences the emergence of safety-critical events and emphasize the importance of diagnostic strategies capable of identifying performance degradation, detecting early-stage faults and predicting impending thermal hazards. Such insights not only enhance safety risk awareness but also enable proactive interventions across the battery lifecycle. Looking ahead, we provide guidance on key pathways toward lifecycle-aware battery management system development and scalable methods for large-scale deployment.

1. Introduction

The surge in greenhouse gas emissions is a primary driver of global climate change, creating urgent energy and ecological challenges [1–3]. At the COP28 conference, world leaders declared a "red alert" on climate deterioration, highlighting the imperative for a rapid transition to low-carbon energy systems [4]. Given that the energy sector is the largest contributor to carbon emissions, its transformation is pivotal for climate change mitigation [5]. Consequently, electrification has emerged as a cornerstone of the global decarbonization strategies across multiple sectors [6,7].

Lithium-ion batteries (LIBs), commercially available for over three decades [8], remain the backbone of modern energy storage systems. Their widespread adoption in consumer electronics, electric vehicles (EVs), and grid storage is largely credited to their high energy density, long cycle life, high operational efficiency and broad temperature tolerance [9,10]. Nevertheless, the growing demand for higher power outputs has raised significant safety concerns [11]. Under varied and often demanding operating conditions, the risk of thermal runaway (TR) escalates; battery-related fires present serious threats to both personal safety and critical infrastructure [12]. Consequently, ensuring the safe and reliable operation of LIBs is critical, highlighting the necessity for real-time monitoring, early fault detection and robust risk assessment methodologies [13,14].

Throughout their lifecycle, LIBs undergo continuous performance and capacity degradation due to repeated cycling, adverse environmental stress, and ageing [15]. This degradation is non-monotonic, and stems from multiple mechanisms, including complex interactions between usage patterns, material composition, and operating conditions [16]. Consequently, LIBs follow distinct ageing trajectories, leading to divergent degradation behaviors and thermal properties at different lifecycle stages [17]. These variations directly influence the triggering conditions and progression of TR, thereby affecting ultimate safety outcomes. As degradation progresses, a battery's tolerance to abnormal

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conditions diminishes, increasing the likelihood of voltage fluctuations, overheating, or internal short circuits (ISCs). Therefore, degradation is intrinsically linked to both performance reliability and operational safety. From a systems perspective, accurate degradation diagnosis and assessment are essential for maximizing battery lifespan and ensuring long-term safety and reliability.

A battery fault is defined as any deviation from expected performance or loss of normal functionality due to internal or external influences during operation [18]. Common manifestations include rapid capacity fade, abnormal voltage behavior, increased internal resistance (IR), electrolyte leakage, and short or open circuits, among others [19]. These faults often originate from material degradation, electrochemical imbalances, mechanical stress, or exposure to harsh environmental conditions such as extreme temperatures [20]. While some faults may directly trigger catastrophic events like fires or explosions, others may seem initially benign yet can evolve into critical failures if not addressed [21]. Therefore, early and accurate fault detection is essential to prevent further deterioration and mitigate safety risks throughout a battery's lifecycle.

TR represents the most severe failure mode in LIBs, characterized by an uncontrollable rise in temperature that can lead to fire, explosion, or complete system failure [22,23]. It is typically initiated by an internal or external trigger, such as overcharging (OC), ISCs, mechanical damage, or thermal abuse, which causes rapid heat generation and accumulation [24]. This resulting temperature increase triggers a cascade of exothermic reactions, including electrolyte decomposition, electrode degradation and gas generation, creating a self-reinforcing feedback loop [25,26]. As these reactions escalate, the intense heat propagates to neighboring cells within a battery pack. TR therefore compromises not only the safety of the battery but also poses significant risks to users and surrounding equipment, underscoring the urgent need for early detection, predictive diagnostics, and effective mitigation strategies.

Managing battery performance and safety throughout its lifecycle requires diagnostic methods tailored to each stage. Understanding the complex relationships between degradation, failure, and TR is thus essential for developing reliable safety strategies. A critical challenge involves characterizing TR behavior across different timescales and degradation states to create robust diagnostics that address both early warning signs and extreme failure modes.

Despite substantial advancements in recent years, several key research challenges remain: (1) how to quantitatively link battery degradation to safety-critical events; (2) how to elucidate the mechanisms that drive the progression from degradation to catastrophic outcomes; and (3) how to establish diagnostic frameworks that comprehensively cover the full spectrum from early degradation to TR. To address these challenges, this review adopts the progression of battery performance throughout its lifecycle as a central narrative framework. Its main contributions include elucidating the electrochemical mechanisms underlying degradation and failure, establishing an end-to-end diagnostic approach covering early degradation, fault evolution and TR risk, and identifying current challenges while discussing promising solutions for safer and smarter battery systems.

In summary, this review emphasizes the critical importance of understanding the fundamental mechanisms underlying battery degradation and TR, as they form the physicochemical basis for interpreting battery behavior and guiding technology development. Building on these mechanistic insights, we explore diagnostic methods for long-term degradation assessment, medium-term fault detection, and short-term TR prediction. By integrating a fundamental mechanistic understanding with advanced diagnostic algorithms, this review highlights the potential of timely and accurate analytics to enhance the safety, reliability and longevity of battery systems.

2. Mechanisms

A thorough understanding of the mechanisms behind battery degradation, abusive failure, and TR is fundamental to advancing the safety and reliability of battery systems. Consistent with this review's time-scale-based safety evaluation framework, we examine these mechanisms across three interconnected domains: degradation, abusive failure and TR.

Degradation mechanisms encompass the intrinsic processes responsible for capacity fade and performance deterioration during normal operation, forming the basis for accurate diagnostics and lifetime prediction. In contrast, abusive failure mechanisms identify the critical triggers, such as electrical, mechanical, or thermal stress, that initiate fault development, thereby enabling early detection and the formulation of targeted prevention strategies. Finally, TR mechanisms provide insight into the uncontrolled onset and propagation of thermal events under extreme conditions, informing the development of predictive models and effective mitigation technologies.

2.1. Degradation mechanisms

LIBs are inherently nonlinear, time-varying electrochemical systems [27]. Through repeated cycling and prolonged usage, they experience performance ageing and degradation, driven by various internal side reactions and external stressors [28]. The most direct manifestations of this degradation are capacity fade and power fade [29]; the former denotes a reduction in the cell's usable energy storage of a battery cell, while the latter indicates a decrease in its deliverable power. Structurally, a LIB comprises four key components: the positive electrode (PE or cathode), negative electrode (NE or anode), electrolyte and separator. Among these, ageing is most strongly influenced by the composition and stability of the PE and NE materials. The specific degradation pathways and side reactions vary depending on the material properties and design of each component. As such, the diversity of electrode chemistries and cell architectures plays a critical role in shaping the overall ageing behavior and degradation dynamics of LIBs.

Graphite is the most common anode material in LIBs, owing to its layered structure that facilitates reversible lithium-ion intercalation and offers a theoretical capacity of 372 mAh/g [30,31]. During initial cycling, side reactions between the graphite and electrolyte form a solid electrolyte interphase (SEI) on the anode surface [32,33]. While this SEI layer is essential for stabilizing the interface, its formation consumes active lithium, and its continued growth during operation further depletes cyclable lithium and increases IR. The repeated volume changes during charge-discharge cycles induce mechanical stress, leading to particle cracking and structural degradation of the anode. Under abusive conditions such as OC or low-temperature operation, lithium plating may occur, where metallic lithium deposits on the NE surface. This can result in dendrite formation, which poses a serious safety risk if dendrites grow through the separator, leading to ISC or TR [34]. Elevated temperatures exacerbate these degradation processes by accelerating side reactions, destabilizing the SEI, promoting lithium loss, and contributing to electrolyte decomposition [35,36], all of which compromise both performance and safety.

In contrast to anodes, cathode materials for LIBs are highly diverse, particularly in electric vehicle (EV) applications where material selection reflects trade-offs among energy density, safety, cost, and longevity [37]. Common cathode chemistries include nickel cobalt manganese oxide (NCM) and nickel cobalt aluminum oxide (NCA), which offer high energy density and are favored for long-range EVs. However, high-nickle NCM formations often exhibit reduced thermal stability [38,39]. Lithium iron phosphate (LFP), by contrast, is known for its excellent thermal stability, intrinsic safety and long cycle life, making it a cost-effective alternative despite its lower energy density [40].

Cathode ageing is primarily governed by two mechanisms: particle cracking and structural decomposition [41]. During cycling, the repeated intercalation and deintercalation of lithium ions induce mechanical stress and volume changes within the cathode particles [42]. These cumulative stresses promote microcrack formation, ultimately

leading to particle cracking. Cracked particles may lose electrical connectivity with the conductive matrix, reducing active material utilization and contributing to capacity fade [43]. Structural decomposition is particularly critical for high-energy-density materials such as high-nickel NCM or NCA [44]. Progressive cycling can cause irreversible changes in the cathode lattice, including oxygen release, cation mixing and phase transitions can destabilize the material's structure [45]. These transformations degrade lithium storage capability and increase the risk of TR, especially under abusive conditions like OC or elevated temperatures. Another prevalent degradation pathway is transition metal dissolution, a common issue in manganese- and nickel-rich cathodes. Dissolved metal ions migrate through the electrolyte and deposit on the anode, where they catalyze SEI decomposition, increase impedance, and accelerate the loss of lithium inventory (LLI) [46,47]. Collectively, these degradation processes diminish energy efficiency, raise polarization, and shorten the battery life. The main degradation mechanisms of the battery are illustrated in Fig. 1.

Based on the distinct degradation modes of the NE and PE, Fig. 2 A illustrates the associated ageing mechanisms and side reactions in LIBs. Common battery ageing modes can be broadly categorized into three types: LLI, loss of active material at PE (LAM_{PE}), and loss of active material at NE (LAM_{NE}) [50]. LLI occurs due to processes that irreversibly consume cyclable lithium, such as lithium plating and dendrite formation, continuous SEI formation, electrolyte decomposition, and transition metal dissolution. These reactions reduce the amount of lithium ions available for shuttling between electrodes [51], leading directly to capacity fade. LAM_{PE} and LAM_{NE} refer to the degradation of active material at the respective electrodes. These losses are primarily caused by active particle cracking, repeated SEI decomposition and reformation, corrosion of current collectors, and dissolution of transition metals. As active material becomes isolated, the battery experiences increased IR, reduced capacity and power output, and accelerated performance fade [52,53]. Furthermore, the dual-tank model (Fig. 2 B) offers an intuitive analogy for representing battery ageing [54]. In this conceptual model, the active material is represented by the tank, and the lithium inventory is represented by the water within it, while charging and discharging are analogous to the transfer of water between tanks.

2.2. Abusive failure-thermal runaway mechanisms

Abusive conditions in LIBs can stem from various sources, such as manufacturing defects, improper usage, or harsh environmental exposure. These factors accelerate performance degradation, shorten battery lifespan, and significantly elevate safety risks [22,56]. Prolonged abuse often triggers complex internal chemical and mechanical changes that can ultimately lead to battery failure [26]. Early failure indicators may include rapid capacity loss, abnormal temperature rise, or voltage irregularities. If unaddressed, the continuous buildup of internal heat and pressure can culminate in TR [57], posing severe safety hazards. Based on the triggering event, battery abuse is typically classified into three categories: mechanical abuse, electric abuse, and thermal abuse [58]. The common forms, causes, and manifestations of three abusive failures in LIBs are summarized in Fig. 3, providing a structured overview of how different abuse modes may initiate or accelerate failure pathways leading toward TR.

Mechanical abuse refers to external physical impacts on LIBs, such as collision, bending, or penetration, commonly resulting from vehicle accidents, poor road conditions, or improper handling and storage. Such mechanical stresses can cause casing deformation, battery swelling, and electrolyte leakage, all of which compromise battery performance. More critically, penetration of the separator can lead to ISCs, triggering abnormal localized heating [59,60]. Additionally, mechanical deformation may induce microcracks in electrode materials, which promote lithium plating and dendrite growth during subsequent cycling. Repeated mechanical abuse can also lead to the formation of internal hotspots, reducing the thermal stability of key components such as the separator and electrolyte, and increasing the likelihood of TR.

Electric abuse includes OC [61], overdischarging (OD) [62], ISCs, and external short circuits (ESCs). These events may be caused by internal manufacturing defects (e.g., impurities that puncture the separator), water immersion, connection failures, or cell-to-cell variations within a battery pack. OC typically leads to lithium plating on the anode, excessive gas generation, and unstable SEI formation, any of which can initiate thermal decomposition reactions [62]. OD, conversely, can result in the dissolution of the copper current collector into the electrolyte, which may then redeposit elsewhere in the cell, potentially forming micro-shorts [63]. In severe cases, electrical abuse can directly lead to TR due to rapid and uncontrolled heat accumulation. Even in milder scenarios, continuous minor electrical abuse contributes to ongoing degradation, such as surface instability and SEI breakdown [64], enlarging the inter-cell inconsistencies and cumulatively shrinking the system's safety margin.

Thermal abuse involves exposing a battery to abnormal internal heat generation or external high-temperature environments. Elevated

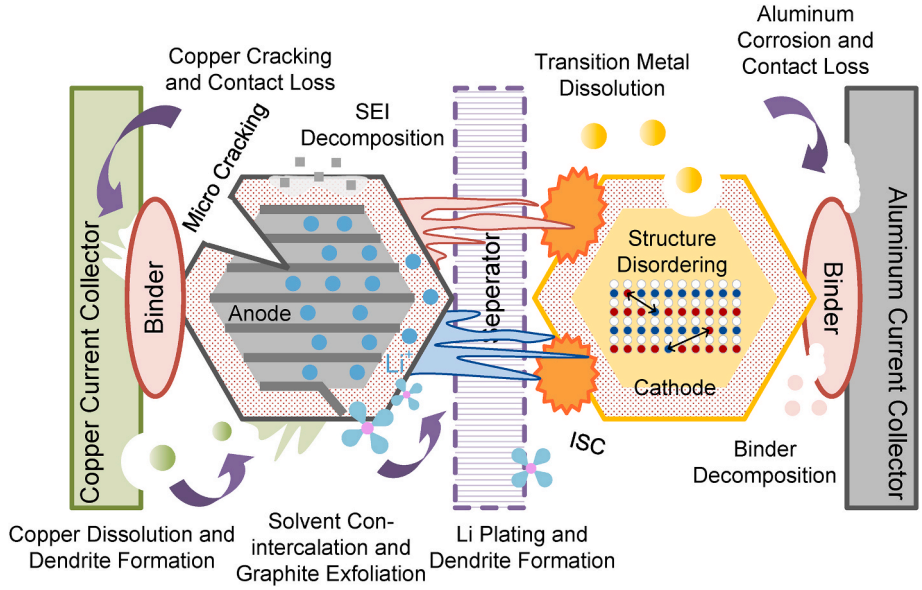


Fig. 1. Dominant degradation mechanisms of LIBs, reproduced from Refs. [48,49].

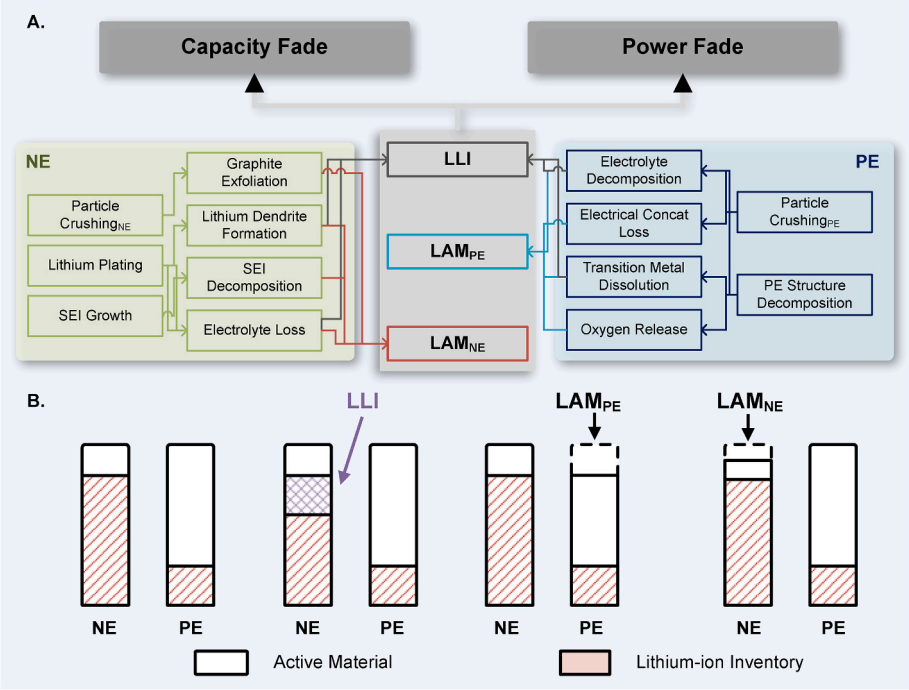


Fig. 2. Representative degradation pathways. A. Degradation modes of LIBs and their corresponding side reactions. **B.** Battery dual tank model, reproduced from Ref. [55] with permission.

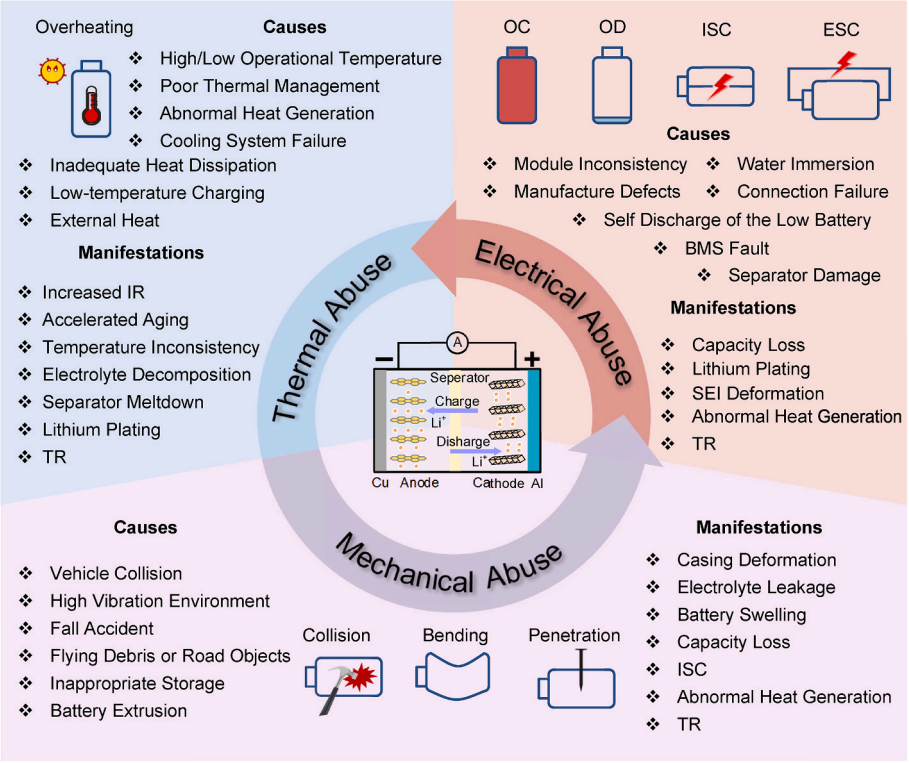


Fig. 3. Common forms, causes, and manifestations of battery mechanical, electrical, and thermal abuse.

temperatures accelerate degradation processes, including decomposition of the electrode and electrolyte, increased gas evolution, and degradation of the separator [65]. Specifically, the electrolyte can undergo exothermic decomposition at high temperatures, while the separator may shrink or melt, compromising its ability to prevent ISCs. As IR increases under thermal stress, operational heat generation intensifies during operation, creating a positive feedback loop that accelerates degradation. This self-reinforcing process, often termed the "onset of TR", can propagate rapidly within a cell, particularly if the separator fails.

Critically, abusive failure modes frequently interact and compound one another. For instance, a mechanical impact that ruptures the

separator can bring the PE and NE into direct contact, triggering an ISC, an event formally categorized as electric abuse. The electric abuse can then evolve into thermal abuse [66], as the ISC generates intense localized heating, effectively creating an internal heat source. Thus, TR is best understood as a thermally driven chain reaction, often initiated by an ISC and sustained by internal exothermic processes. A TR state occurs when the rate of heat generation within the battery exceeds the rate of heat dissipation [67]. Consequently, ISCs should not be viewed as isolated electrical or mechanical phenomena, but as critical convergence where mechanical, electrical, and thermal abuses interact [68,69].

Fig. 4 illustrates the chain reaction mechanism underlying TR in a LIB with NCM/Graphite electrodes [70]. As the cell temperature rises, a sequence of exothermic and degradation processes is initiated. The initial stage involves the decomposition of the SEI on the anode begins to decompose, which compromises its protective function and can induce internal stress , potentially leading to rupture of the SEI layer. With further temperature increase, the exposed anode reacts with the electrolyte solvent, initiating a strong exothermic reaction. Concurrently, the separator begins to melt, and the NCM cathode decomposes, releasing oxygen. The evolved oxygen rapidly reacts with the electrolyte, further accelerating heat generation. This reaction cascade culminates in an ISC, causing a rapid voltage drop. The combination of the ISC and sustained exothermic reactions leads to a sharp temperature spike and the rapid release of stored chemical energy, potentially driving the battery into full TR. This state is characterized by violent gas release, electrolyte combustion, and potential cell rupture. Current TR research defines several critical thermal thresholds to characterize this progression: Onset temperature (T_1): The point at which the cell temperature rise rate exceeds 0.02 °C min^{-1}, indicating the beginning of thermal instability; Triggering temperature (T_2): The threshold where the rate of the temperature rise exceeds 1°C s^{-1}, marking the initiation of TR; Maximum temperature (T_3): The peak temperature reached during the event, representing the thermal extreme of the failure process. These thresholds (T_1, T_2, T_3) are influenced by multiple factors. Cell chemistry is critical; nickel-rich NCM or NCA cells typically exhibit lower T_1 and T_2 thresholds, along with a higher T_3, compared to LFP cells. The SOC significantly affects severity, as cells at high SOC contain more energy, leading to an earlier T_1 and a faster temperature rise. The triggering method also introduces additional variability; external heating, penetration, and overcharge typically accelerate decomposition reactions and lower T_1/T_2 compared to controlled thermal ramping. Furthermore, the health state of the cell also impacts these thresholds, as aged cells generally exhibit altered thermal stability compared to fresh ones.

2.3. From degradation to thermal runaway

The degradation of LIBs not only affects performance but also fundamentally influences their safety evolution, particularly the onset and progression mechanisms of TR. TR refers to the uncontrolled release of internal energy, driven by a cascade of exothermic reactions under elevated temperatures. When the rate of heat generation exceeds the battery's dissipation capacity, thermal imbalance occurs, which, when combined with self-accelerating chemical reactions, can escalate into catastrophic outcomes such as fire or explosion [71]. The susceptibility to reactions is strongly dependent on the battery's degradation state. As LIBs degrade, they become structurally more fragile and increasingly susceptible to thermal, mechanical, and electrical stresses. To be specific, as reported in Ref. [72], cycle ageing primarily weakens the mechanical strength of the separator, rendering the cell more susceptible to ISC-induced TR under mechanical abuse. Interfacial ageing, including SEI deterioration, lithium dendrite formation, and the accumulation of unstable by-products, lowers the T1 for self-heating, thereby facilitating earlier occurrence of self-heating-triggered TR. Capacity fade, although often associated with a reduction in the total heat output, can lead to higher peak temperatures during thermal events in aged cells, resulting in more intense thermal responses and aggravated TR. Furthermore, the operational history, such as exposure to high or low temperatures and mechanical stresses, can alter the total heat release and heat generation rate during TR, ultimately influencing both its severity and evolutionary pathways. For instance, fast charging promotes lithium plating that triggers TR at lower onset temperatures, whereas slow charging results in higher onset thresholds. And Zhang et al. [73] revealed that low-temperature cycling and high-rate cycling accelerate the increase of temperature rise rate and irreversible heat, thereby exacerbating thermal risks at an early stage; in contrast, high-temperature cycling and high-temperature storage have minimal impact in the early stages, but thermal risks increase significantly during the later stages of ageing. Literature [74] demonstrated that dynamic cycling combined with calendar ageing lowers the trigger temperature, making TR more likely to occur. And Jia et al. [75] pointed out that under mechanically induced conditions, ageing delays the triggering of ISC due to capacity fade, while soft ISC events occur more frequently, mainly dictated by the mechanical behavior of the current collectors. These effects are mainly caused by degradation-induced phenomena, including dendrite growth, unstable interfacial species, and intensified side reactions. In summary, different ageing modes can modify the triggering conditions of TR, influence the initiation pathways such as ISC, self-heating, and interfacial reactions, and reshape the evolution characteristics including heat release, peak temperature, and generation rate, thereby leading to distinct manifestations of TR, highlighting that degradation and ageing

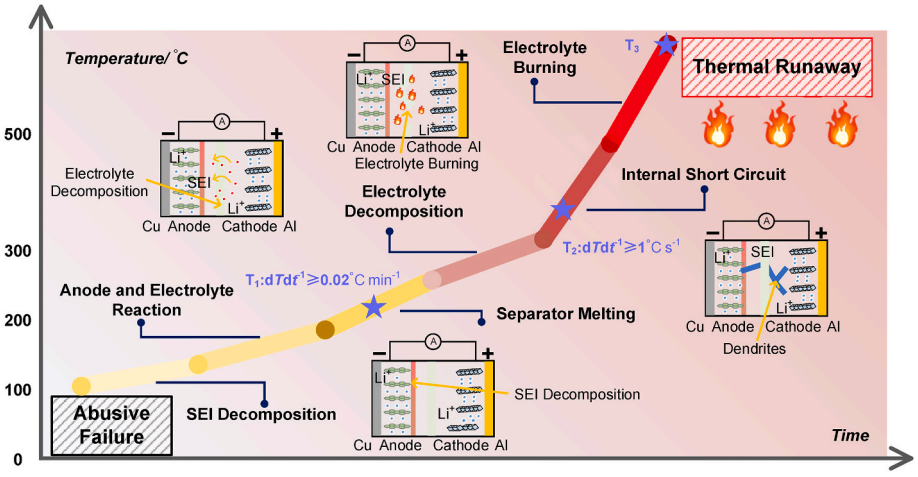


Fig. 4. Qualitative interpretation of the chain reaction during TR of LIBs with NCM cathode.

history plays a critical role in shaping the thermal hazard profile of LIBs throughout their lifecycle.

And to reflect the varying dynamics of TR events and their relationship with degradation stages, we propose a safety evolution framework that categorizes TR into two typical types: progressive TR and sudden-death TR.

Progressive TR evolves gradually and is typically associated with internal degradation processes or micro-faults. These include the slow growth of lithium dendrites, the gradual breakdown and reformation of the SEI layer, and the mechanical weakening of electrode materials over prolonged operation. Such processes often incrementally degrade the internal structure of the battery, resulting in localized heat generation and accumulation. As thermal energy builds over time and exceeds the dissipation threshold, the battery eventually crosses a critical temperature limit, triggering TR. The delayed onset and slower heating profile of progressive TR provide a valuable window for early-stage detection and preventive intervention. As such, accurate degradation diagnosis and timely fault detection are essential for risk mitigation and the safe extension of battery service life.

In contrast, sudden-death TR is characterized by an extremely rapid onset, typically triggered by foreign matter introduced during manufacturing [76] or by acute external stresses such as mechanical shock, severe OC, or electrical ISC. These events initiate an immediate and violent reaction within the cell, leading to a sharp and uncontrollable temperature spike [77]. The defining feature of sudden-death TR is its near-instantaneous onset, within seconds to minutes, or at most a few hours, key parameters such as temperature and voltage can exceed critical thresholds. This rapid progression is driven by a series of highly exothermic reactions, often accompanied by the generation of flammable gases and, in extreme cases, visible flames or explosions. Existing battery safety algorithms struggle to provide timely detection of sudden-death TR. Specifically, in some cases, the battery exhibits no detectable faults before the event, as exemplified by copper-metal-induced sudden-death TR, where deposited copper triggers an Al–NE ISC without any preceding abnormal behavior. Notably, even when minor faults are present, such as micro ISC or lithium plating, the associated signals are extremely weak, making sudden-death TR hard to detect. Limitations in sensor placement, data resolution, and data volume often prevent these subtle indicators from being detected by current diagnostic algorithms. Consequently, the abruptness and intensity of sudden-death TR leave minimal opportunity for predictive diagnostics or internal mitigation, highlighting the critical importance of external protective systems and fast-acting safety responses.

Fig. 5 illustrates a comparative overview of the progressive and sudden-death TR, highlighting differences in timescales, observable manifestations and mitigation strategies. This classification emphasizes the diverse safety risks that LIBs face across different stages of degradation and underscores the critical importance of degradation monitoring, fault detection and rapid response in lifecycle-wide safety management. By establishing safety evaluation within a unified "Degradation diagnosis–Fault detection–TR prediction" paradigm, this work not only provides mechanistic insights into the onset and evolution of TR but also offers a foundation for developing stage-specific safety control strategies. This dual-mode classification not only enhances the understanding of battery degradation and safety issues over time but also provides a comprehensive analysis of the mechanisms leading to TR, guiding the implementation of targeted diagnostic and protective measures throughout the battery's operational life.

3. Diagnostics

Building on the internal reaction mechanisms of LIBs discussed in Section 2, this section focuses on diagnostic strategies throughout the battery lifecycle. We review recent advances in degradation diagnosis, fault detection, and TR prediction, organizing them along a time-scale perspective. This approach aligns diagnostic methods with specific stages of battery ageing, supporting accurate, timely, and application-relevant safety assessments. By mapping diagnostics to distinct phases of the battery's lifespan, a structured framework is established to guide full-life-cycle performance evaluation and safety management.

3.1. Diagnosing embryonic problems in battery degradation

Battery degradation and safety are intrinsically interconnected, as the progressive deterioration of battery performance significantly influences the likelihood of safety-critical events. As batteries age, issues such as capacity fade, increased IR and reduced thermal stability become more pronounced, elevating the risk of ISC, TR, and gas generation. Accurate degradation diagnosis is therefore essential for assessing safety across the full battery lifecycle, providing critical insight into the mechanisms driving both performance decline and safety vulnerabilities. This section reviews state-of-the-art methods for degradation diagnosis, emphasizing the critical link between degradation and safety. It also highlights the importance of integrating accurate diagnostic strategies into battery management systems (BMSs) and implementing preventive measures to ensure both performance and safety throughout the full lifecycle of LIBs.

Degradation in LIBs is typically quantified through capacity fade and increased IR, which together define the battery's state of health (SOH). A battery is generally considered to have reached its end of life (EOL) when its capacity decays to 80 % of the original value or when its IR has doubled. In the context of battery-powered EVs, where driving range is a key performance metric, SOH is commonly represented by the ratio of current useable capacity to the initial capacity. Both SOH estimation and

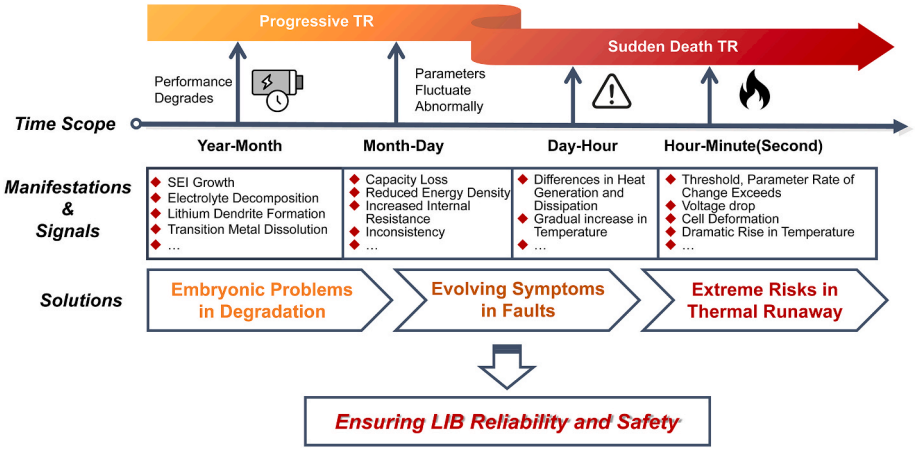


Fig. 5. Relationship, manifestations and signals of progressive TR and sudden death TR from the perspective of battery diagnostic time scope.

degradation trajectory prediction are critical for understanding battery performance, enabling lifetime forecasting, proactive maintenance, and safety risk assessment. These methods can be broadly categorized into three main types: experimental methods, model-based methods, and data-driven methods.

3.1.1. Experimental methods

Experimental methods determine the SOH and ageing mode by directly measuring battery performance parameters under controlled conditions. Techniques such as electrochemical impedance spectroscopy (EIS) [78] provide diagnostic insight by analyzing the impedance spectrum to capture health-related characteristics. Similarly, capacity measurements determine SOH by comparing actual and nominal capacities [79], while IR measurements offer a straightforward indicator of degradation. In addition, the open circuit voltage (OCV)-SOC curve characterizes the nonlinear voltage response of LIBs across different SOC levels, and changes in this curve can reflect electrochemical ageing. SOH estimation involves periodically measuring OCV at specific SOC levels and comparing the profile to a reference from a healthy cell [1]. Features such as inflection points, slope variation, and voltage deviation across SOC ranges are analyzed to infer capacity fade or IR growth [80,81]. While these experimental methods are widely regarded as the gold standard for offline validation due to their reliability and physical interpretability, they are time- and resource-intensive. Consequently, they are generally unsuitable for real-time, embedded, or large-scale applications.

3.1.2. Model-based methods

Model-based methods describe the ageing process by using mathematical models to simulate the internal behavior of LIBs. Two primary modeling approaches are commonly employed: electrochemical models (EM) and equivalent circuit models (ECM). EM, such as pseudo-two-dimensional (P2D) models [82], simulate internal chemical reactions in batteries, such as lithium-ion diffusion, electrode polarization, and electrolyte transport. These models enable SOH estimation by ageing-related parameters, such as active material loss, lithium inventory decay, or SEI growth. Although highly accurate and grounded in physical mechanisms, their complexity and high computational demand make them challenging for real-time onboard diagnostics. Additionally, to account for battery ageing, the Doyle–Fuller–Newman (DFN) model is integrated with additional sub-models that mathematically represent degradation mechanisms, including SEI growth, lithium plating, active material loss, and particle cracking. Specifically, a physics-based model integrating degradation mechanisms within the DFN framework has been developed in PyBaMM [83]. This multi-mechanism coupling reveals multiple usage-dependent degradation pathways, offering insights for lifetime prediction and design, though parameterization remains a major challenge. In contrast, ECM simplifies the battery cell using idealized electrical components, such as resistors, capacitors and voltage sources, to represent key electrochemical processes. By mapping physical phenomena to electrical analogs, ECMs offer a balance between physical relevance and computational efficiency. On this basis, model-based methods often incorporate parameter estimation techniques, such as particle swarm optimization (PSO), recursive least squares (RLS), Kalman filtering (KF), simulated annealing (SA), or genetic algorithm (GA) to infer SOH-related parameters [84,85]. Typically, this process involves three steps: computing the residual between measured and predicted voltage, defining an objective function based on the residuals, and applying optimization techniques to iteratively refine model parameters. Despite their advantages, model-based methods face challenges, including approximation errors due to model simplification, reliance on high-precision measurements, and computational overhead when modeling complex or dynamic systems, limiting their use in embedded applications.

3.1.3. Data-driven methods

Data-driven approaches differ from the methods mentioned above in that they do not rely on predefined mathematical models [86]. Instead, they infer the relationship between battery features and degradation directly from laboratory [87] or field data [88] using machine learning (ML) or deep learning (DL) algorithms. These methods are particularly well-suited for nonlinear degradation modeling under real-world operating conditions, where complex interactions are difficult to capture using traditional models. A crucial step in this process is the extraction of degradation-sensitive features from raw battery data. Early methods leveraged direct statistical features and signal processing techniques, such as the mean, variance, and entropy of charging voltage [89,90], skewness and kurtosis of temperature distributions [91]; and variations in constant-current/constant-voltage (CC/CV) charging durations [92]. For instance, Zhang et al. [93] extracted 12 direct features from multi-stage CC charging voltage curves for real-world SOH estimation in EVs. Signal-processing techniques like incremental capacity analysis (ICA) and differential thermal voltammetry (DTV) have been widely used for feature extraction. ICA, which analyzes the derivative of capacity with respect to voltage, reveals ageing-related shifts in electrochemical behavior but typically requires a fixed low charging current, limiting its applicability. She et al. [94] explored the second peak in the IC curve of the LFP batteries, demonstrating its strong correlation with battery performance degradation and applicability to real-world electric buses' SOH estimation. DTV evaluates the temperature–voltage relationship by calculating dT/dV during CC charging, enabling thermal degradation analysis. While DTV offers more flexibility in charging rate, it is sensitive to ambient temperature fluctuations. Tian et al. [95] have reported DTV during CC charging to be highly related to battery SOH and this method is more flexible in terms of charging rate requirements, but is strongly affected by environmental temperature.

To relate extracted features to battery degradation, statistical methods such as linear regression and Gaussian process regression (GPR) [96] have been applied. One study [97] developed a linear regression-based SOH estimator using fast-charging data, achieving a prediction error of 1.09 % and maintaining SOC estimation error within 5 %. Steininger et al. [88]proposed an unsupervised framework that clustered batteries with similar ageing conditions and used statistical learning to detect abnormal SOH estimates from large-scale field data. It flagged 98 % of anomalies, highlighting the effectiveness of statistical learning for reliable ageing assessment. These statistical approaches offer flexibility, adaptability and the ability to model nonlinear relationships, with the added benefit of interpretability in some cases. However, they also come with drawbacks: dependence on large labeled datasets, sensitivity to outliers, potential overfitting, and increased computational cost when training complex models. Typical data-driven degradation frameworks incorporating these techniques are illustrated in Fig. 6.

With the rapid advancement of data acquisition technologies and the availability of large-scale battery datasets from both laboratory experiments and the field, ML and DL approaches have gained substantial traction for battery SOH estimation. ML models such as support vector machines (SVM), random forests (RF) and gradient boosting decision trees (GBDT) [101] have become popular due to their strong predictive capabilities and ability to extract degradation-sensitive features from complex datasets.

Unlike traditional ML methods, DL algorithms excel in processing high-dimensional and time-series data without requiring manual feature engineering. Recurrent neural networks (RNNs), for instance, are well-suited for capturing long-term dependencies in charge/discharge cycles, enabling end-to-end SOH prediction under dynamic conditions [102]. Tian et al. [103] demonstrated the application of deep neural networks (DNN) to reconstruct entire charging curves using only partial charging curves as input. Lu et al. [104] further extended this by estimating battery SOH without labeled data from the target system, leveraginglab datasets from 65 commercial battery cells across five

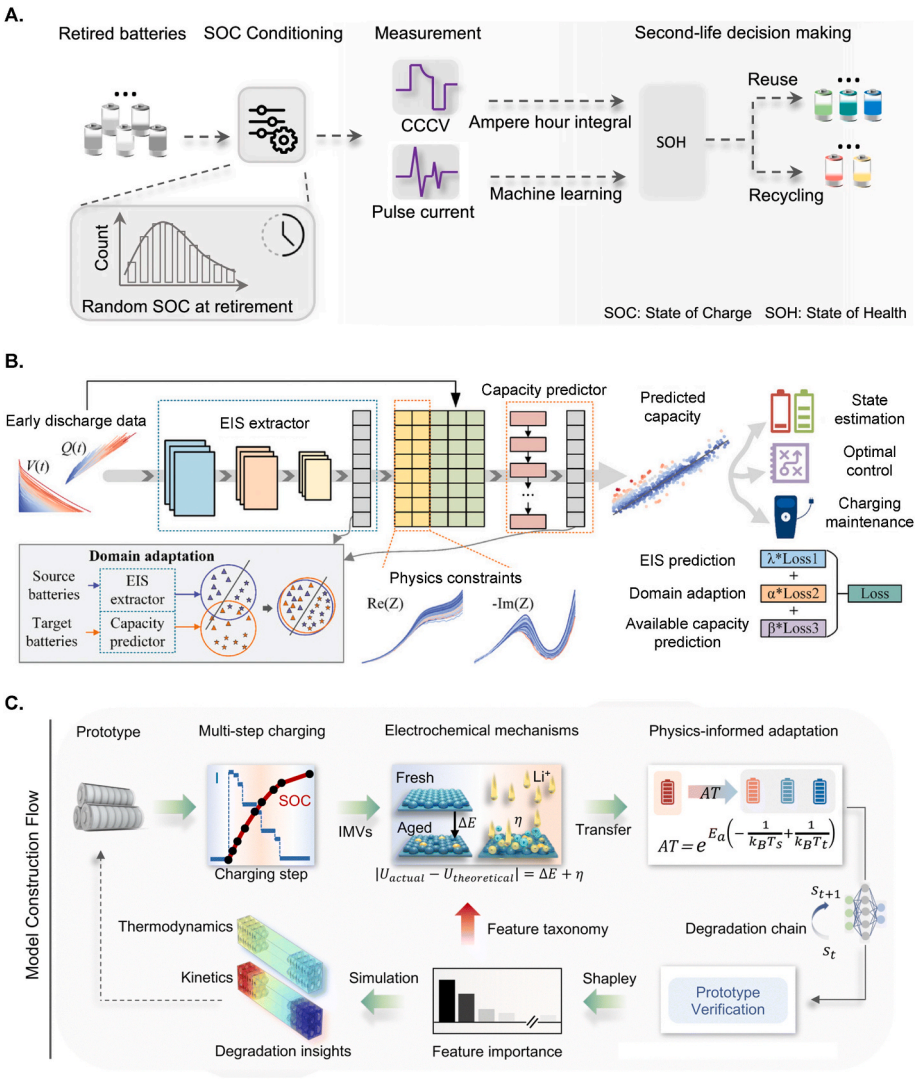


Fig. 6. Typical data-driven frameworks of battery degradation diagnosis. A. the general framework for data-driven battery degradation diagnosis, reproduced from Ref. [98]; B and C. are innovative physical-data fusion battery degradation diagnosis frameworks, adapted from Refs. [99,100] with permission.

manufacturers.

The applicability of DL in real-world field scenarios has also been well demonstrated [105–107]. Wang et al. [108]combined instantaneous and statistical features extracted from large-scale field data of battery systems, utilizing a sequence-to-sequence long short-term memory (LSTM) network to diagnose battery degradation with uncertainty. Similarly, Deng et al. [109] proposed a convolutional neural network (CNN)-based method for rapid SOH estimation using only short-duration charging data with limited labeled samples. Xiang et al. [110] introduced a semi-supervised biGRU-SKI model, which leveraged dynamic discharge features, including current rate, pseudo-differential voltage, and temperature, to achieve root mean percentage errors (RMSPE) of less than 3.24 % using only 1.5 %–15 % labeled data under realistic conditions.

Despite these promising developments, data-driven methods face several key challenges. Their performance is highly dependent on the quality, quantity, and diversity of available data. DL models require significant computational resources and long training time, which can hinder their deployment in resource-constrained BMSs. Moreover, many DL models operate as "black boxes," offering limited interpretability and making it difficult to link predictions to underlying physical mechanisms. A summary of representative degradation diagnosis methods is presented in Fig. 7.

In parallel with the growth of the purely data-driven methods, physics-informed neural networks (PINNs) [111] have emerged as a promising hybrid approach that integrates battery physics into data-driven SOH estimation to enhance interpretability and generalizability [112,113]. By embedding physical constraints and governing equations into neural network architectures, PINNs aim to overcome the “black-box” limitations of conventional DL models while maintaining predictive accuracy. Tao et al. [100] proposed a physics-informed learning model designed to address the complexities and uncertainties in battery manufacturing. Their approach enables the non-destructive quantification and visualization of temporally resolved thermodynamic and kinetic parameters derived from electrical signals. By statistically analyzing current intensities and switching conditions in a multistep charging protocol, the model supports material-agnostic feature extraction and predictive modeling of battery lifetime trajectories. Despite these advancements, degradation diagnosis through physics–data fusion remains an open challenge. Many of the limitations associated with purely physical models, such as sensitivity to uncertain working conditions, difficulty in parameter calibration, and limited generalizability across battery chemistries, persist in hybrid methods. The integration of physics-informed modeling into real-world battery systems still faces obstacles related to data variability, computational complexity, and the diversity of operating environments, particularly in

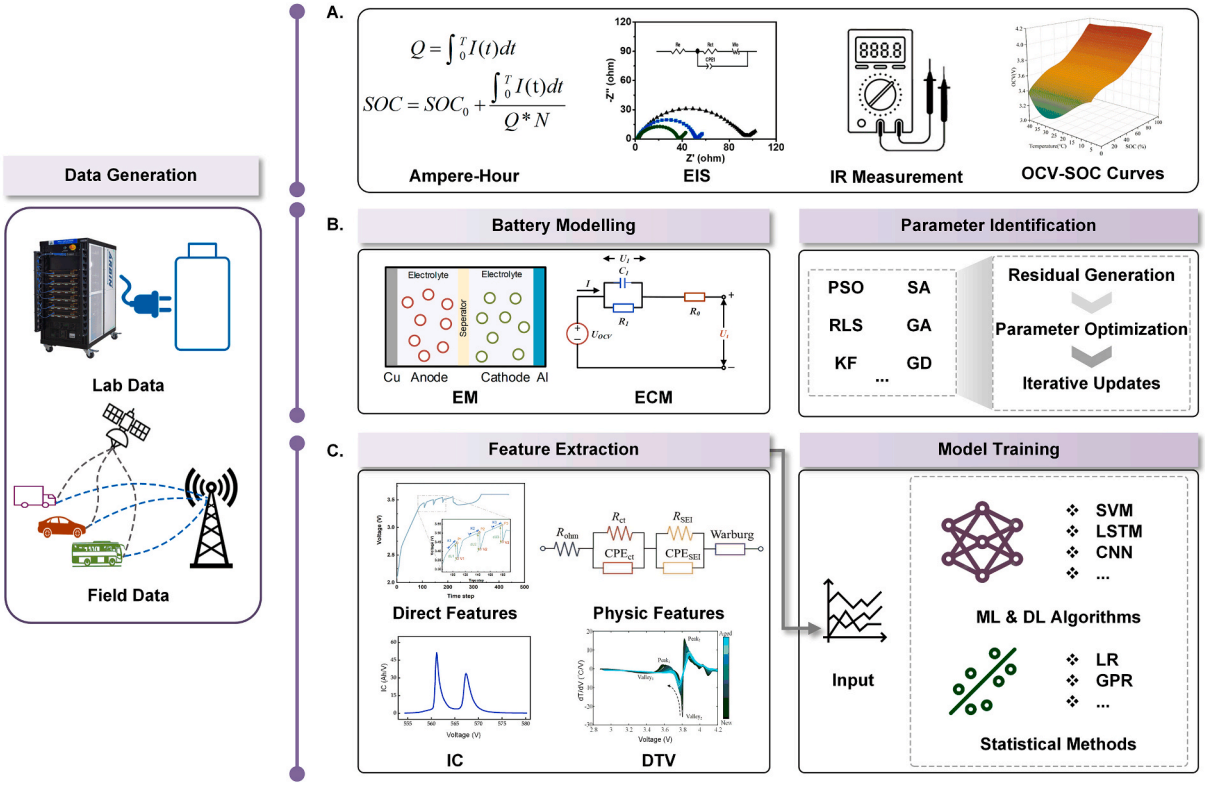


Fig. 7. General framework of battery degradation diagnosis. A, **B**, and **C** represent experimental, model-based and data-driven methods, respectively.

large-scale or in-field applications.

As presented in Table 1, experimental, model-based, and data-driven approaches exhibit distinct strengths and inherent limitations in diagnosing battery degradation. Experimental methods provide benchmark-level accuracy and exceptional interpretability by directly probing electrochemical phenomena; however, their dependence on specialized instrumentation and controlled environments makes them impractical for real-time or onboard applications. Model-based techniques offer a balanced compromise between accuracy and interpretability, extracting physically meaningful parameters from accessible signals such as voltage, current, and temperature. Yet, their performance is highly sensitive to model fidelity, and high-resolution electrochemical models can impose prohibitive computational costs. Data-driven methods demonstrate strong adaptability and high predictive accuracy when supported by comprehensive and representative datasets, making them highly attractive for practical deployment. Nevertheless, their limited interpretability and occasionally high computational demands, particularly for DL architectures, remain key challenges.

Overall, selecting an appropriate diagnostic strategy requires careful consideration of accuracy, interpretability, data requirements, and computational feasibility. These trade-offs have driven a growing interest in hybrid and adaptive diagnostic frameworks that integrate physics-based modeling with data-driven learning to achieve both robustness and scalability.

3.2. *Detecting evolving symptoms in battery faults*

Battery failures primarily result from complex electrochemical reactions during operation and the diversity of external conditions. Specifically, improper usages such as OC, OD, excessive current, or extreme temperatures can damage the internal structure, while manufacturing defects, external mechanical damage, BMS faults, connection faults, sensor faults, and cooling system faults, etc., may also cause failures directly or indirectly. In many cases, battery system faults are closely linked to abnormal or accelerated degradation processes. For instance, unexpected lithium plating, SEI growth, or structural damage caused by uneven ageing may evolve into functional failures over time. Early-stage micro-faults are usually subtle and initially pose minimal risk. However, if not diagnosed and addressed promptly, these micro-faults can progressively worsen, potentially leading to TR, fire, or even explosion. Hence, immediate detection and mitigation of potential failures can prevent accidents and protect user safety. Battery fault diagnosis methods can be broadly classified into knowledge-based, model-based, and data-driven methods.

Table 1
Comparison of battery degradation diagnosis approaches.

Method Category	Accuracy	Data Requirement	Interpretability	On-board Feasibility	Computational Complexity
Experimental	Very High (benchmark level)	Low	Very High	Low (offline only)	High (time- and resource-intensive)
Model-based	Medium–High (model fidelity dependent)	Medium	High (clear physical basis)	Medium (simplified models feasible)	Medium (ECM low, EM models high)
Data-driven	High (requires sufficient representative data)	High	Low–Medium (black-box nature)	High (lightweight models can be deployed)	Medium–High (ML low, DL very high)

3.2.1. Knowledge-based methods

Research on knowledge-based battery fault diagnosis began early and has been widely applied. These methods draw on expert experience, rule sets, or logical reasoning derived from historical observations of battery behavior. This type of method does not require the use of complex mathematical models, but instead performs fault reasoning and judgment through the application of knowledge of concepts and processing methods. Knowledge-based battery fault diagnosis methods specifically include fault tree analysis (FTA), expert system method and rule-based fault diagnosis. FTA [114] employs logical tree models composed of top events (system failures) and base events (root causes) linked by AND/OR gates to probabilistically analyze failure causality chains; however, its reliance on expert knowledge limits its dynamic adaptability. Expert systems [115] excel in handling uncertainties from multi-source, heterogeneous data by constructing an inference mechanism based on a knowledge base. This method relies on domain expert knowledge to identify abnormal conditions and fault types. However, its diagnostic capability depends on the completeness and accuracy of expert knowledge, making it challenging to cover all possible fault patterns. Rule-based methods are widely adopted in-vehicle remote monitoring platforms, relying on predefined static or dynamic thresholds (e.g., temperature, voltage fluctuations), which enable rapid fault alerts with low computational costs. However, they suffer from false alarms in nonlinear time-varying systems due to the rigidity of these thresholds. Ref [116] proposed a three-rule-based overcharge fault determination and warning system through charging experiments on ternary LIBs. Meanwhile, the 19 alarm rules defined in Chinese National Standard GB/T 32960 (e.g., temperature, voltage thresholds) are widely adopted by EV companies. Overall, knowledge-based methods provide strong interpretability, low data dependency and the ability to customize rules for specific battery types or operating conditions, which makes them suitable for particular application scenarios. However, the diagnostic capability is limited by the completeness and accuracy of expert knowledge, making it difficult to handle complex data and restricting their generalization ability.

3.2.2. Model-based methods

Model-based fault diagnosis methods utilize mathematical representations of battery behavior to estimate key values and compare them with actual measurements, generating system residuals from the differences for fault detection and identification. These residuals serve as characteristic signals of faults and can be further analyzed to extract fault features, providing theoretical and data support for system fault diagnosis. In model-based approaches, fault diagnosis and SOH estimation both utilize ECM or physical models (as illustrated in Section 3.1), but their applications differ significantly. Fault diagnosis primarily focuses on anomaly detection, often relying on residual analysis and parameter drift monitoring. For example, abrupt changes in ECM parameters such as IR and polarization resistance can indicate risks like ISC or further TR. Additionally, physical models (e.g., P2D models) can predict lithium plating formation [112], providing early warnings of potential ISC failures. Model-based fault diagnosis emphasizes the rapid identification of short-term anomalies, whereas degradation estimation focuses on the precise prediction of long-term degradation trends. Chen et al. [117] adopted Luenberger observers and learning observers to isolate and estimate faults in multi-cell batteries under uncertainties. By reorganizing the system into fault-specific observer banks, faults were isolated via residual analysis and estimated through learning observers. Ref [118] proposed a two-layer model-based fault diagnosis algorithm for ESC. The first layer screening is performed by setting two conditions: cutoff voltage and peak current. The second layer screening utilizes the PSO algorithm to identify the parameters of a first-order ECM. Based on the root mean square error (RMSE) threshold, the method can achieve ECM diagnosis within 5 s. Ref [119,120] employed a mean difference model combined with extended KF to estimate the deviation of the SOC of an individual cell from the average SOC within a battery pack. This deviation was then processed using an RLS to develop a method for diagnosing micro-ISC in batteries, enabling precise detection of ISC resistance. In summary, model-based approaches offer real-time high accuracy and interpretability for fault detection, but are also limited by the complexity of model development, high computational cost, and strict requirements for precise parameter calibration. Therefore, this approach is currently challenging to apply in solving diagnostic challenges using real-world operational battery data.

3.2.3. Data-driven methods

In recent years, data-driven fault diagnosis has emerged as a focal point in advanced battery research. These approaches rely on battery measurement data to detect patterns and anomalies without explicitly using physical models or expert rules. ML and statistical techniques are employed to infer relationships directly from historical or real-time data. Data-driven methods can generally be categorized into signal processing-based approaches and ML or DL-based approaches. Typically, the basic performance parameters of individual cells in a fault-free battery pack are consistent. When some of the cells in a battery module fail, the most direct manifestation is the inconsistency of the cell parameters. Battery fault diagnosis methods based on signal processing essentially diagnose anomalous signals generated by the inconsistency of individual cells in a battery module, analyzing morphological and statistical characteristics of time-series battery data. In curve similarity-based approaches, battery profiles are constructed from individual cells, with cosine similarity or dynamic time warping (DTW) used to quantify morphological consistency between the target and reference waveforms. Wu et al. [121] developed a rapid ISC detection method by applying cosine similarity in LFP battery modules, where a two-dimensional feature vector was constructed from battery voltage and current data to achieve effective fault-signal separation. Additionally, entropy theory focuses on signal complexity, where battery profiles are segmented into windows and sample entropy [118,119], fuzzy entropy, and relative entropy [120] are used to evaluate local randomness. Fault-induced nonlinear disturbances manifest as abnormal entropy fluctuations. After extracting fault features by empirical mode decomposition, Li et al. [122] adopted the sample entropy to detect several battery faults by capturing the off-trend voltage drop under various operation conditions. Correlation analysis identifies outlier cells by computing correlation coefficients or mutual information between battery sequences across battery modules. Normal cells exhibit near-unity correlations, whereas faulty cells show reduced correlations due to IR shifts or capacity fade, which enables the subsequent fault isolation. Xia et al. [123] introduced a voltage correlation-based approach for ISC fault detection in series-connected battery modules, leveraging Pearson correlation analysis to identify abnormal inter-cell voltage relationships. By statistically evaluating pairwise voltage correlations, this method isolated ISC-affected cells through deviations in normalized correlation coefficients, enabling targeted fault localization. Signal processing-based methods enable real-time monitoring and interpretable fault diagnosis by correlating waveform distortions, signal complexity, or key inter-cell parameter deviations with failure mechanisms, eliminating the need for complex electrochemical models. These methods require minimal labeled data and excel in detecting localized anomalies or nonlinear disturbances. However, their performance is highly condition-dependent: dynamic operating profiles may introduce phase misalignment in similarity analysis, necessitating computational alignment algorithms, while inherent cell inconsistencies can obscure correlation-based fault localization.

Clustering methods play a crucial role in ML/DL-based battery fault diagnosis by identifying the outliers as faulty cells from normal cells. As an unsupervised learning approach, clustering algorithms can automatically discover latent structures in data, making them effective even in the absence of labeled fault data. Common clustering techniques include K-Means, density-based clustering (DBSCAN), and Gaussian Mixture Models (GMM), which group battery data based on voltage,

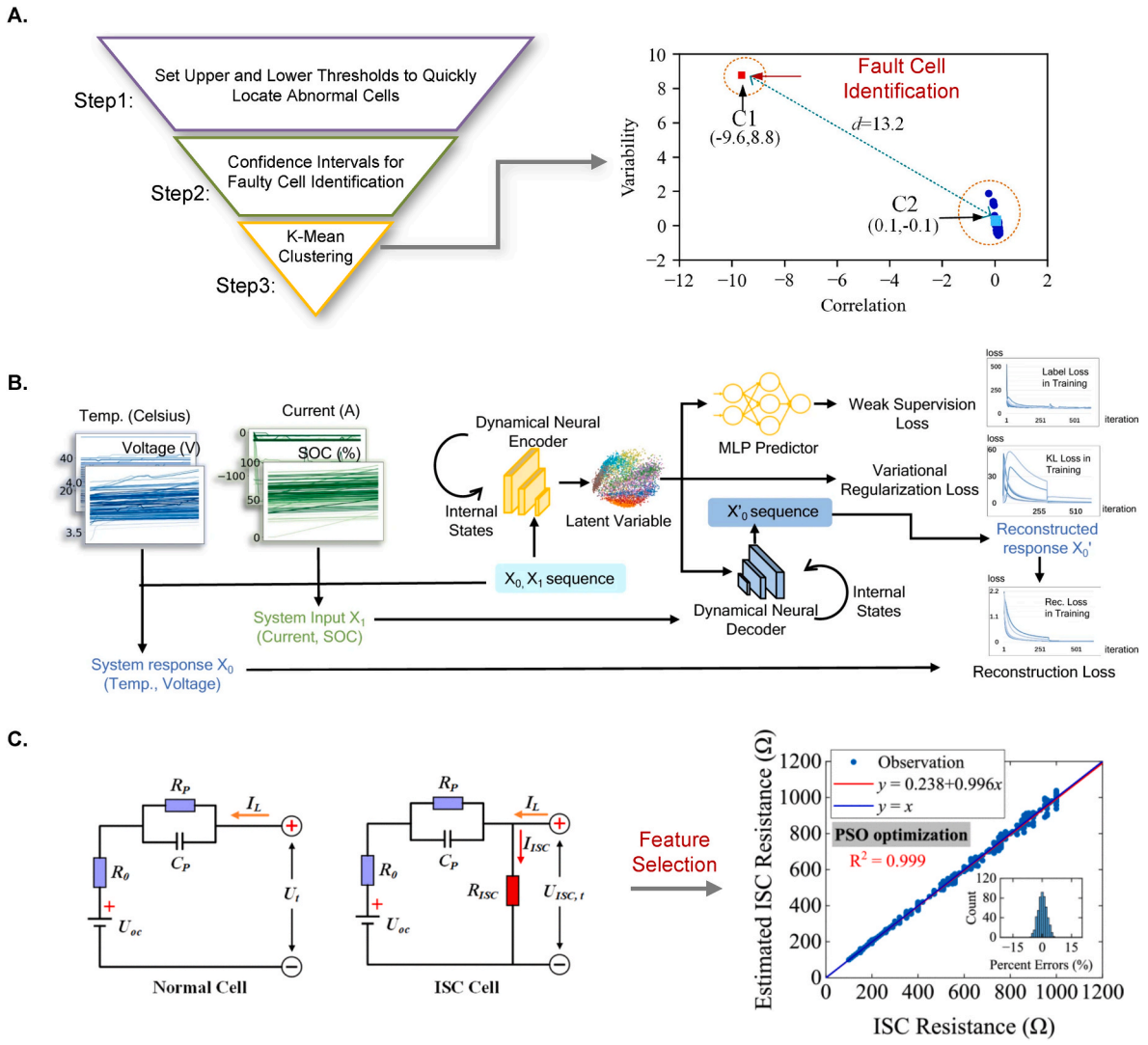


Fig. 8. Typical data-driven frameworks of battery fault diagnosis. A. shows a clustering-based three-layer battery voltage fault detection framework, reproduced from Ref. [124] with permission; **B.** is an autoencoder-based anomaly diagnosis strategy adapted from Ref. [131]; **C.** analyzes the ISC faults through ECM and estimates the IR through data-driven modeling, thus enabling ISC diagnosis, reprinted from Ref. [132] with permission.

current, temperature, IR, and other multidimensional features to distinguish between normal and faulty states. As shown in Fig. 8 A, Sun et al. [124] proposed a three-layer battery fault detection framework, utilizing threshold-based monitoring, confidence interval calculation and improved K-means clustering to identify voltage abnormalities and potential failures, validated through real-world EV operational data. A combined symplectic geometry mode decomposition and two-dimensional feature clustering based on DBSCAN in Ref. [125] was constructed to detect the battery fault in time, with only one parameter under a wide range of values. Liang et al. [126] proposed a self-organizing mapping neural network combined with an adaptive threshold to enhance the practical applicability for battery fault diagnosis and inconsistency evaluation of the battery module in real-world applications. In summary, this method is effective in identifying outliers in battery modules and does not require labeled data. However, despite their promising performance, clustering-based methods face challenges such as high-dimensional data processing and sensitivity to parameter selection. Furthermore, since the early manifestations of faults are very subtle and hidden, they may be difficult to distinguish from normal cells, which limits the performance of clustering-based methods.

In addition, supervised classification frameworks necessitate the availability of meticulously annotated datasets where fault categories are explicitly labeled, while residual analysis methodologies typically leverage the statistical characteristics of deviations between model predictions and empirical measurements to identify anomalies. Reference [127] proposed a method based on the RF classifier to detect electrolyte leakage in ESC batteries. By utilizing two features, maximum temperature rise and minimum discharge capacity, the classifier is trained with a large amount of labeled data to determine the leakage status. The study [128] developed an ML-based fault diagnosis method for electrolyte leakage in LIBs. A cloud-based IC bar graph method and a simplified subspace identification algorithm were used to extract key features, which are fed into a multi-classifier fusion decision framework. This approach quantifies fault severity and achieves up to 26 days of early warning. Zhao et al. [129] proposed a cloud-based multi-classifier framework integrating GBDT and Attention-enhanced CNNs. GBDT extracts critical features from voltage/temperature curves, while CNNs capture temporal dynamics. This hybrid classifier achieved 96.3 % accuracy in identifying early-stage failure patterns of asymptomatic batteries, with 7.7 % misclassification error. Key innovations include physics-informed feature selection and adaptive attention mechanisms for cross-cycle pattern recognition. Concisely, classifier-based battery fault diagnosis methods offer high accuracy, adaptability to nonlinear

problems and the ability to identify multiple fault types. They are data-driven and scalable across different battery applications. However, they rely heavily on large, high-quality datasets, often lacking labeled fault data in real applications. They also require careful feature selection and often lack interpretability, especially DL models. Additionally, they may struggle with new fault types and have high computational costs.

Predictor-based battery fault diagnosis utilizes predictive models to estimate key battery parameters, detect anomalies, and forecast potential failures, providing a proactive approach to battery management and safety assurance [111]. By leverageing ML/DL algorithms and hybrid methodologies, these approaches capture complex fault mechanisms and dynamic electrochemical behaviors, enabling early and accurate fault identification. Unlike classification-based methods that rely on predefined fault categories, predictor-based diagnosis continuously adapts to evolving battery conditions, making it particularly effective in real-world applications where labeled fault data is scarce. Zhang et al. utilized a temporal convolutional network (TCN) [130] to diagnose the ISC fault of LIBs by estimating the battery voltage under normal conditions using an adaptive threshold algorithm to account for dynamic changes in external operational conditions. Researchers from Tsinghua University [131] developed a method based on a dynamical autoencoder specifically designed for LIB anomaly detection in EVs. The framework processes real-world battery charging data (over 690,000 snippets from 347 EVs) to configure the model architecture. The autoencoder dynamically adapts to evolving battery states by learning latent representations of charging dynamics, enabling anomaly detection without relying on predefined fault signatures as highlighted in Fig. 8 B. Qiao et al. [132] designed a data-driven method using GPR with PSO-optimized relaxation voltage features to achieve $<$6.45 % error in early ISC diagnosis, as illustrated in Fig. 8 C. To provide a more precise and more structured comparison beyond a chronological discussion, we summarize the key characteristics of the main data-driven fault diagnosis approaches in Table 2. The comparison considers algorithm families, data requirements, diagnostic accuracy, real-time feasibility, as well as the advantages and limitations of each method.

However, achieving high diagnostic accuracy requires precise model calibration, robust feature selection and effective strategies for handling uncertainties introduced by measurement noise, environmental fluctuations and variations in operating conditions. To address these challenges, integrating physics-informed models with data-driven predictors enhances interpretability and reliability by combining theoretical insights with empirical learning. Furthermore, adaptive learning techniques, including transfer learning and domain adaptation, facilitate model generalization across different battery chemistries, ageing states and usage scenarios. The fusion of predictive analytics with real-time BMSs not only improves fault prognosis but also enables condition-based maintenance strategies, ultimately enhancing the longevity, safety and economic viability of battery-powered systems. For a more precise understanding, we have developed a general framework for battery fault detection, as shown in Fig. 9.

3.2.4. Multi-fault diagnosis

Nowadays, many studies have proposed diagnostic methods for single battery faults. However, in practical applications, due to the uncertainties of the external environment and operation modes of EVs, various types of battery failures often occur simultaneously, with characteristics that are hidden and similar. Diagnostic methods that focus on a specific type of fault are often insufficient for the comprehensive assessment of battery system safety risks. To address the challenge of diagnosing multiple simultaneous faults, researchers have adopted cross-topology circuits to measure voltages across different configurations. This measurement strategy highlights unexpected voltage differences across cells or modules, aiding in the distinction between different types of battery faults. A fault simulation and cross-topology circuit is shown in Fig. 10 A. And a general multi-fault diagnosis framework is concluded in Fig. 10 B.

Building on cross-topology circuits, experiments are designed to simulate multi-fault scenarios and observe the resulting fault phenomena. Researchers employ tools such as the correlation coefficient (CC) and entropy theory to identify the type of fault and locate the faulty battery cell without requiring a battery model. These methods utilize signal processing to transform subtle data profiles into clear, computationally interpretable results for anomaly detection. Studies[133–135] have shown that various types of faults produce distinct changes in the CC between measurement points. Similarly [136–139], have demonstrated that entropy theory can effectively identify and differentiate multiple faults. However, these methods typically require cross-topology measurements, which demand more sensors compared to one-to-one sensor arrangements, raising barriers in real-world applications.

Without cross-topology measurement, researchers utilize ML/DL or battery models to establish relationships between battery external parameters and internal states, realizing battery fault distinction. Our previous work [140] proposed a DL-based multi-fault diagnosis and safety evaluation framework that uses directly measurable parameters, as illustrated in Fig. 10C. This framework combines future reference

Table 2
Summary of data-driven fault diagnosis methods for LIBs.

Method	Representative Techniques	Data Requirements	Accuracy	Real-Time Feasibility	Advantages	Limitations
Signal Processing-based	Curve similarity, entropy theory, correlation analysis	Voltage, current, temperature time-series (cell/module level)	Moderate to High	High	● Requires minimal labeled data- Interpretable ● Low computational cost	● Performance sensitive to dynamic profiles ● Alignment needed for phase shifts ● Cell inconsistency may obscure results
Clustering-based	K-Means, DBSCAN, GMM	Multivariate features: voltage, current, IR, temperature	Moderate	Moderate	● No labeled data required ● Effective for outlier detection ● Scalable to large datasets	● Sensitive to parameter tuning ● Poor performance with subtle/hidden early faults ● High-dimensionality challenge
Classifier-based	RF, GBDT, CNN,	Large labeled datasets (fault categories) + engineered features	High	Low to Moderate	● High accuracy ● Handles nonlinear relationships	● Requires large, high-quality labeled data ● Limited interpretability ● Computationally expensive
Predictor-based	Autoencoder, TCN, GPR, hybrid ML-physical models	Sequential/charging data, sometimes partial labels	High	Moderate	● Works with scarce labels ● Captures evolving battery dynamics ● Enables early detection	● Requires robust calibration ● High computational complexity in real-time

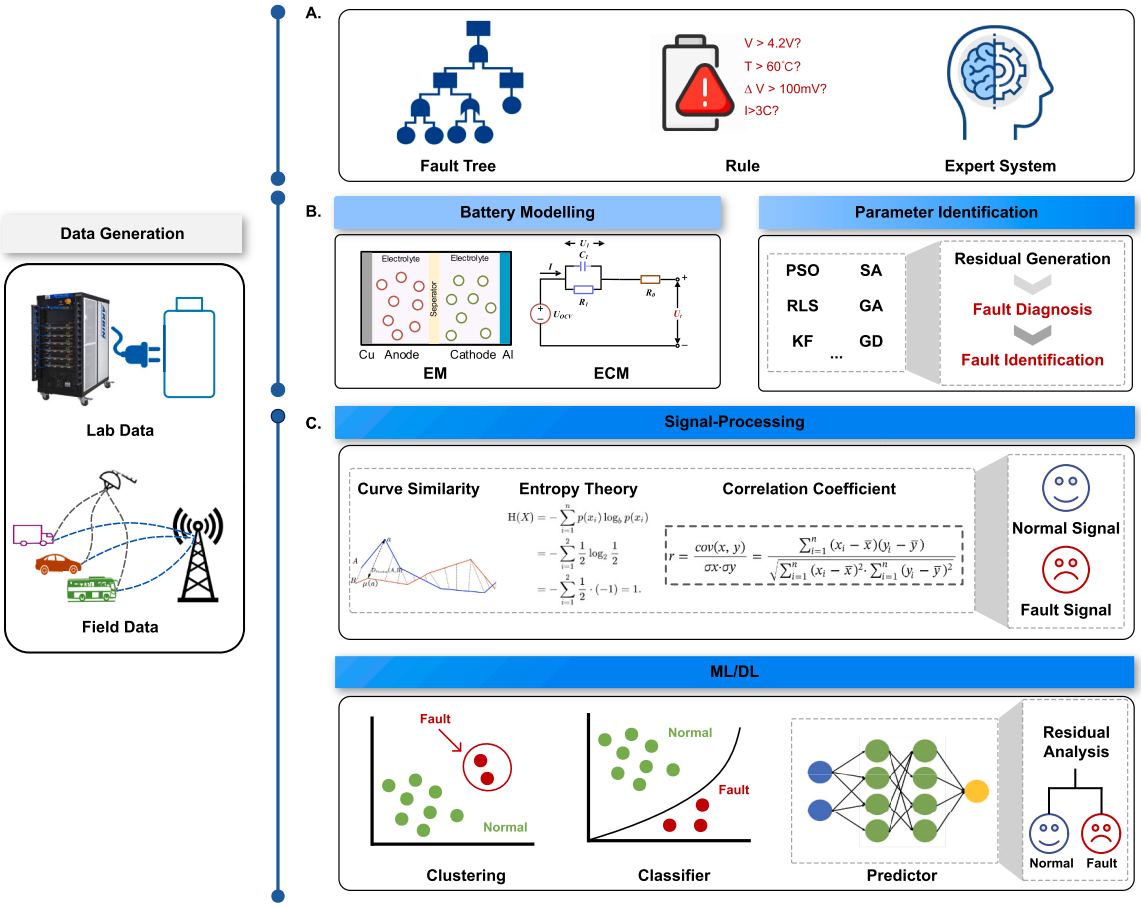


Fig. 9. General framework of battery fault detection. **A**, **B**, and **C** represent knowledge-based, model-based, and data-driven methods, respectively.

voltage prediction with an effective classifier to identify and predict multiple faults and has been validated on real-world operating battery data. Cai et al. [141] introduced a category-reinforced domain adaptation network for transfer learning to diagnose various faults, including voltage imbalance, ISC, sensor faults, sensor drift voltage and random fluctuations. Ma et al. [142] demonstrated a method combining Z-score normalization and KF to preprocess battery voltage data for enhanced anomaly feature extraction, followed by DBSCAN clustering to autonomously detect localized anomalies, including micro ISC, low capacity and low electric quantity, with differentiation achieved through anomaly duty cycle analysis during charging phases, effectively resolving detection confusion caused by overlapping voltage patterns.

In summary, advanced multi-fault diagnosis in battery systems typically involves establishing a threshold gradient through model-based or non-model-based methods. This enables both the differentiation of fault types and the quantification of fault severity, laying the foundation for timely maintenance and safety assurance. However, some challenges remain: (1) Redundant interleaved voltage measurement topologies that detect faults via CC analysis, but their complexity and sensor requirements limit real-world BMSs' applicability; (2) Fault labels are often missing in real-world data, making practical multi-fault diagnosis challenging.

3.3. Identifying high-risk states toward thermal runaway

Battery TR is the most extreme and unsafe form of battery failure. It occurs when the internal temperature of a LIB rises uncontrollably, leading to a chain reaction of exothermic events that can cause catastrophic outcomes such as fires, explosions, and the release of toxic gases. This phenomenon is typically triggered by factors such as OC, ISC, or mechanical damage, which cause excessive heat buildup within the battery. As the temperature rises, the electrolyte decomposes and the cell's components can react violently, further escalating the heat. TR is especially dangerous because it can spread rapidly across multiple cells in a battery pack, compromising the safety of entire systems. Understanding and predicting TR are critical to ensuring the safe operation of batteries in applications like EVs and large-scale energy storage systems. Here, we review TR prediction methods by categorizing them into two main approaches: extreme abuse testing-based and real-world incidents-based methods.

3.3.1. Extreme abuse testing-based methods

As a method to simulate the working environment of batteries under extreme conditions, extreme abuse testing mainly studies the thermal behavior and TR mode of batteries by applying excessive current, OC, ISC, overheating, etc. Through these tests, the safety of batteries under extreme working conditions can be effectively evaluated. Various methods have been developed to identify early signs of TR and prevent catastrophic failures, with a primary focus on monitoring battery behavior leading up to TR. Among these, three key approaches have been widely explored: tracking internal characteristic parameters, analyzing thermal behavior, and detecting gas emissions. These methods provide essential insights into battery safety by identifying precursors to TR and enabling timely intervention measures.

Monitoring internal characteristic parameters is one of the most fundamental and widely adopted methods for predicting TR. This approach relies on real-time tracking of battery voltage, current, temperature, pressure, and other parameters to detect abnormal conditions

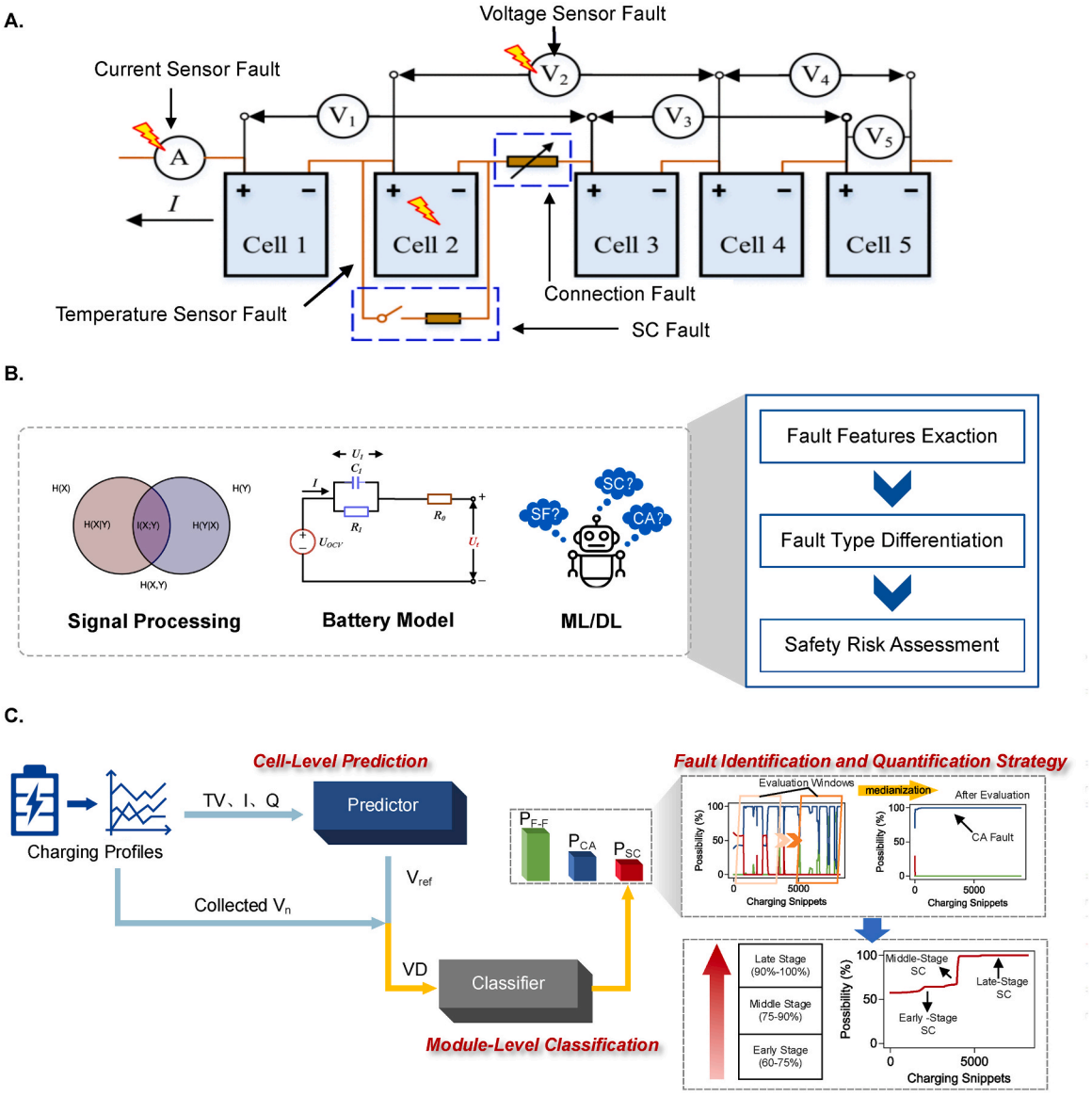


Fig. 10. Overview of circuits and frameworks for battery multi-fault diagnosis. A. A multi-fault simulation circuit [134]. **B.** General framework of battery multi-fault detection. **C.** A DL-driven multi-fault diagnosis flowchart [140].

that may indicate impending failure. Voltage fluctuations, for example, often serve as an early warning of internal degradation. OC leads to excessive voltage, which accelerates side reactions, promotes dendrite formation and increases the risk of ISC. Similarly, abnormal current patterns, such as sudden spikes or irregular variations, may signal ISC or unstable electrochemical reactions. Temperature monitoring is another critical aspect of this method, as excessive heat accumulation is a direct precursor to TR. Under normal conditions, the battery temperature remains within a controlled range; however, an unexpected temperature rise without a corresponding increase in load suggests internal heat buildup due to self-heating reactions or electrolyte decomposition. Jia et al. [143] construct a comprehensive dataset linking mechanical strain states to safety outcomes across various cell types, charge states and loading conditions, as shown in Fig. 11 A. Jia et al. [144] developed an internal temperature-driven TR warning strategy for LIBs using embedded thermocouples and an adaptive thermal correlation model as demonstrated in Fig. 11 B, achieving detection 18–22 min earlier than surface monitoring through dynamic core temperature estimation. The model resolved critical thermal gradients through environment-dependent linear scaling, while maintaining consistent slope characteristics across various operational conditions. By integrating a finite element mechanical model with ML, the approach achieves high-accuracy safety risk prediction, demonstrating the potential of combining physics-based and data-driven methods for energy storage system safety assessment. Mei et al. [145] proposed a submillimeter multifunctional optical fiber sensor for operando TR monitoring in 18650 LIBs, surviving extreme conditions while simultaneously tracking internal temperature and pressure dynamics. The system enables ≥120s pre-vent TR warnings through characteristic differential curve inflection detection, identifying critical transitions between reversible/irreversible reactions via dual pressure peaks and optical signal correlations. Ref [146] demonstrated that expansion force monitoring enables 110s-earlier TR detection than voltage/temperature signals in commercial $LiNi_{0.5}Co_{0.2}Mn_{0.3}O_2$ and LFP cells under abuse scenarios, as displayed in Fig. 11C, showing a 2200 % force variation correlating with the TR severity hierarchy, providing priority response thresholds through preload force-derived metrics. In addition, some studies have used coupled signals or novel sensing technologies for TR prediction.

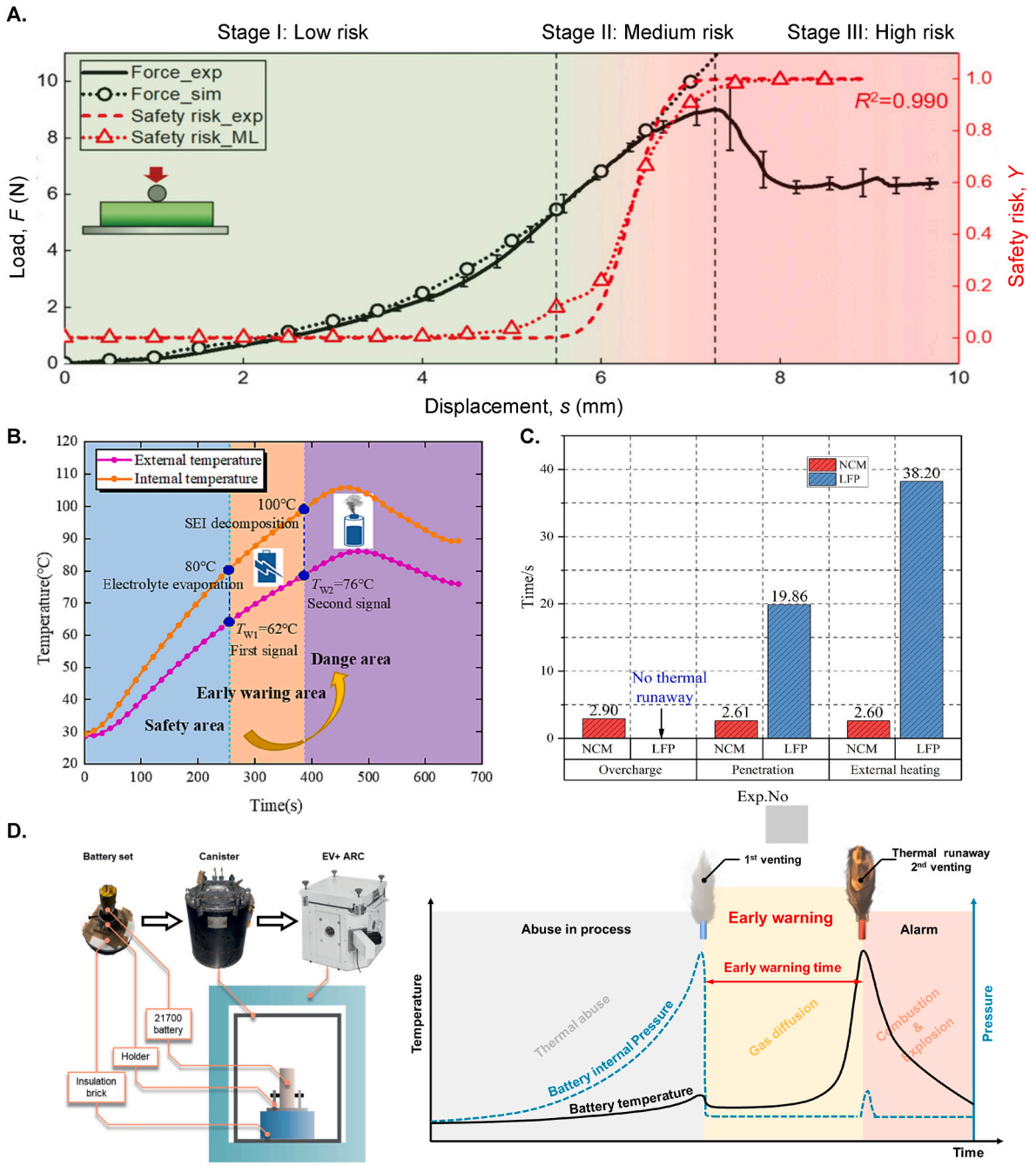


Fig. 11. Typical TR prediction frameworks. A. mechanical stress-based method, adapted from Ref. [143]; B. temperature-based method, reproduced from Ref. [144]; C. expansion force-based method, reproduced from Ref. [146]; D. gas emission-based method, reprinted from Ref. [149].

Cheng et al. [147] achieved early TR prediction in prismatic batteries through a multi-physics monitoring strategy combining customized cover-plate-integrated pressure sensors and temperature-pressure coupling analysis. Experimental results demonstrated 42.7 % earlier warning capability compared to temperature-only methods, with identified critical pressure thresholds 11–50 % lower than standard values under thermal abuse conditions, enabling non-invasive detection through synergistic analysis of gas dynamics and thermal signatures.

Additionally, gas emission detection is an emerging technique for predicting TRs, focusing on identifying early-stage chemical reactions within LIBs. Before TR occurs, LIBs undergo electrolyte decomposition and electrode degradation, producing gaseous byproducts such as carbon dioxide (CO_2), carbon monoxide (CO), hydrogen (H_2), methane (CH_4) and hydrogen fluoride (HF). By monitoring and analyzing these gases in real-time, researchers can detect early risk processes before they escalate into TR, providing an additional layer of predictive capability beyond tracking electrical and thermal parameters. Studies have established correlations between gas emissions and specific TR stages [147], demonstrating that CO_2 and CO levels increase during the initial stages of electrolyte decomposition, while hydrogen generation becomes significant at elevated temperatures. By correlating these gas composition trends with temperature dynamics, predictive models can estimate the probability of TR based on characteristic emission patterns. Liu et al. [148] developed a dual-stage acoustic early warning strategy for LIB TR by fusing multi-domain acoustic features. Experimental validation demonstrated 98.08 % recognition accuracy in 18650 cells, achieving non-invasive alerts 9352 s earlier than conventional temperature and pressure-based methods through millisecond-level acoustic

response to covert TR initiation. Huang et al. [149] developed a 3D TR model and gas diffusion framework, correlating internal pressure dynamics with initial venting signals to predict battery failure, enabling over 20 s of early warning and offering a critical tool for designing gas-driven TR mitigation systems as illustrated in Fig. 11 D. This approach is particularly advantageous for applications where early detection is critical, such as electric devices and large-scale energy storage systems. However, challenges remain in the large-scale implementation of this technique, particularly in terms of sensor sensitivity, response time and integration with existing battery monitoring systems.

In summary, the prediction of TR is crucial for ensuring the safety and reliability of LIB-powered applications. Current methods primarily focus on monitoring electrical and thermal parameters, analyzing heat accumulation patterns and detecting gas emissions to identify early warning signs of TR. Each approach has its strengths and limitations: parameter monitoring is widely used for real-time detection but may not capture early-stage degradation mechanisms; thermal analysis provides insights into heat-driven failure processes but often reacts to already elevated temperatures; and gas emission detection offers a unique means of identifying chemical degradation but requires sensitive instrumentation for practical implementation. To improve TR prediction accuracy, researchers are increasingly combining multiple detection methods to leverage their complementary advantages. The integration of multi-sensor monitoring, ML-based data analytics and predictive modeling will play a vital role in advancing TR early warning systems. Future developments in sensor technology and data-driven diagnostics will further enhance LIB safety, contributing to the widespread adoption of electric mobility and renewable energy storage.

3.3.2. Real-world incident-based methods

The TR prediction methods based on extreme abuse testing typically rely on test data collected under extreme conditions in laboratory settings, aiming to simulate the battery behaviors under overuse or extreme environmental factors, such as excessively high charge/discharge rates or extreme temperatures. These tests help researchers understand the TR characteristics of the battery under extreme conditions and evaluate its safety in such scenarios. However, the representativeness of this data is somewhat limited, as it does not account for the battery's performance in everyday use and real-world environmental conditions. In contrast, TR prediction methods based on real vehicle data are more relevant to practical applications, as they rely on data collected from actual driving environments, which account for various factors such as temperature fluctuations, driving patterns, and battery usage history. These methods provide a more accurate reflection of the battery's thermal management and safety in typical usage scenarios, offering greater practical value. Therefore, in the following section, we will review TR prediction methods based on real vehicle data, exploring how integrating real-world usage data can enhance the accuracy and reliability of TR predictions. Currently, many researchers have conducted a series of TR prediction studies using real-world battery TR data. These studies mainly rely on information extracted from sensor data of EVs during operation, such as temperature, voltage and current parameters, combined with ML and data analysis techniques to achieve early warning and prediction of battery TR.

Li et al. [150] proposed a data-driven approach for battery TR prognosis in EVs, combining modified XGBoost for temperature prediction and PCA-DBSCAN for abnormality detection. The method achieves accurate 5-min forward temperature prediction with reduced errors and provides a 35-min forward prognosis, offering sufficient response time to minimize risks. Yu et al. [151] developed a multimodal framework that combines time, frequency and IR features with unsupervised learning, enabling TR prediction up to a week in advance, validated across diverse real-world batteries via a unified threshold for accuracy and generalizability. Cao et al. [152] utilized a DL-based online diagnostic network that integrates battery model constraints and a stochastic system evolution framework to enable real-time fault detection under unpredictable operating conditions. The network was sensitive to detecting electrolyte leakage, ISC, excessive ageing and TR, while remaining adaptable to diverse battery pack structures to reduce implementation costs. Ref [153] innovatively constructed a novel unsupervised early TR detection algorithm, combining multi-feature clustering and hierarchical warnings. The algorithm extracts cell features, applies unsupervised iterative scoring using clustering and a sliding window technique and implements a hierarchical warning mechanism based on real-time scoring, extending the warning time for abnormal cells by over ten days compared to conventional BMSs.

However, methods based on real-world data face several challenges, such as data scarcity, noise interference and nonlinear relationships between variables. These factors complicate model training and validation. Nevertheless, with the development of big data technologies and ML algorithms, more research is now attempting to use real-world data for efficient TR prediction, making significant progress. Through these data-driven approaches, researchers are better able to understand the triggering mechanisms of battery TR and provide strong safety guarantees for EVs.

3.4. Gathering LIB dataset sources

In recent years, an increasing number of battery-related open-source datasets have been made available to the research community, greatly promoting the development of data-driven modeling, diagnostics and prognostics. These datasets primarily focus on the battery ageing process, covering long-term cycling data under various operating conditions and have been widely used in studies on battery health estimation and degradation modeling. In addition to degradation-related data, some datasets have begun to include information on TR and safety-critical events, offering valuable insights into battery behavior under abusive conditions. However, open-source datasets specifically dedicated to battery safety issues, such as early-stage fault evolution, thermal propagation and failure characterization remain relatively limited.

In this section, we systematically gather the currently available open-source battery datasets as illustrated in Table 3, providing a comprehensive resource for researchers in the field. By categorizing these datasets based on key attributes, such as data source, brief introduction, and potential utilization cases, we aim to provide valuable insights into their applicability for various research objectives. We particularly highlight several unique and representative battery datasets that stand out due to their innovative design or novel application scenarios. These datasets are valuable not only for evaluating battery performance and modeling degradation but also for advancing safety research. Importantly, by summarizing datasets related to both degradation and safety, we hope to bridge the gap between these two research domains and promote integrated approaches for understanding the interplay between long-term degradation and safety-critical failures.

(1) Battery failure databank

Finegan et al. [154] from the National Renewable Energy Laboratory (NREL) have open-source datasets containing hundreds of abuse tests designed to induce TR across various commercial LIB designs and testing conditions. And they employed a method known as fractional TR calorimetry, which quantifies not only the total heat released but also the specific heat contributions from the cell casing and the ejected materials during TR. Moreover, the team captured high-speed synchrotron radiography videos to visualize the internal dynamic responses of cells during TR. The resulting dataset serves as a valuable tool for analyzing and understanding battery thermal behavior. For instance, they identified correlations between the fraction of mass ejected from cells, the total heat output and the energy and power density of the cells. These insights helped explain the thermal variations observed among different cells during TR. This dataset provides valuable assistance for researchers studying TR. By quantifying the total heat released during TR and its

Table 3
Summary of existing public battery datasets.

Dataset	Source	Description	Utilization	Data Link	Refs
University of Tokyo	Lab	Small pouch cells tested via ARC for thermal stability and heat generation	TR prediction	https://static-content.springer.com/esm/art%3A10.1038%2Fs41560-025-01751-7/MediaObjects/41560_2025_1751_MOESM2_ESM.xlsx	[157]
Tsinghua	Real-World	Datasets comprising over 690,000 LIB charging snippets from 347 EVs	Fault detection & TR prediction	https://figshare.com/articles/dataset/Realistic_fault_detection_of_Li-ion_battery_via_dynamical_deep_learning_approach/23659323	[131]
Beihang	Real-World	A dataset of 18.2 million valid entries from 515 vehicles collected by a cloud-based data center	Fault detection & TR prediction	https://static-content.springer.com/esm/art%3A10.1038%2Fs41467-025-56832-8/MediaObjects/41467_2025_56832_MOESM3_ESM.zip	[152]
NREL	Lab	Data collected from hundreds of abuse tests conducted on commercial LIBs	TR prediction	https://www.nrel.gov/transportation/battery-failure.html	[158–162]
Changan Automobile	Real-World	300 operational vehicles with a mileage range of 0–500,000 km	Degradation diagnosis	http://ivstskl.changan.com.cn/?p=2697	[163]
LINKE	Real-World	28 LFP battery systems with a nominal 160Ah capacity; Data spans 1 month to 5 years per system.	Degradation diagnosis	https://zenodo.org/records/14562266	[164]
NASA	Lab	Datasets include Li-ion battery cycling data across various temperatures and impedance as a degradation metric.	Degradation diagnosis	https://data.nasa.gov/dataset/Li-ion-Battery-Ageing-Datasets/uj5r-zjdb/about_data	[165–170]
CALCE	Lab	Datasets contain long-term cycle ageing data for LIBs tested under controlled charge/discharge conditions with varying temperatures, DOD, and current rates.	Degradation diagnosis	https://web.calce.umd.edu/batteries/data.htm	[103]
OXFORD	Lab	Datasets include long-term ageing tests of 8 pouch cells cycled in a thermal chamber at 40 °C.	Degradation diagnosis	https://ora.ox.ac.uk/objects/uuid:03ba4b01-cfed-46d3-9b1a-7d4a7bdf6fac	[171]
RWTH	Real-World	Time-series data from onboard loggers of 9 EVs operating in commercial geriatric care fleets in Germany	Degradation diagnosis	https://git.rwth-aachen.de/isea/battery-degradation-trajectory-prediction	[172]
RWTH	Real-World	21 residential PV-coupled battery systems in Germany, measured over 8 years	Degradation diagnosis	https://zenodo.org/records/12091223	[173]
MIT/Stanford	Lab	Dataset includes 124 LFP cells cycled to failure under various fast-charging protocols.	Degradation diagnosis	https://data.matr.io/1/projects/5c48dd2bc625d700019f3204	[89]
Cambridge	Lab	Dataset includes EIS measurements from 88 lithium-ion coin cells cycled under randomly varied charging/discharging currents to simulate realistic uneven usage.	Degradation diagnosis	https://zenodo.org/records/6645536	[174]
INL	Lab	Dataset includes 12 sets of charge/discharge cycling data for NMC 811 cells with varying formulations, cell configurations, and testing protocols.	Degradation diagnosis	https://osf.io/2w4k3/	[175]
UESTC	Real-World	The charging data of battery packs from 20 commercial EVs spans over two years	Degradation diagnosis	https://github.com/TengMichael/battery-charging-data-of-on-road-electric-vehicles/	[176]
NDANEV	Real-World	Massive real-world operation EV data	Degradation diagnosis & Fault detection & TR prediction	http://new-openlab.ndanev.com:32411/	[177]
TJU	Lab	Dataset includes cycling, impedance and voltage relaxation data from three types of commercial 18650 batteries.	Degradation diagnosis	https://zenodo.org/records/6405084	[178]
Cambridge	Lab	Dataset enables ML-based analysis of degradation mechanisms in LIBs using EIS.	Degradation diagnosis	https://zenodo.org/records/3633835	[179]
Imperial	Lab	Dataset includes raw and processed data with analysis code for studying the degradation of Li-ion battery packs under thermal gradients.	Degradation diagnosis	https://zenodo.org/records/10207731	[180]
TUM	Lab	The dataset includes pre-trained weights from the ARCANA framework trained across LIBs and sodium-ion battery chemistries.	Degradation diagnosis	https://zenodo.org/records/10293072	[181]
XJTU	Lab	A total of 55 batteries were tested under six different charge-discharge strategies.	Degradation diagnosis	https://wang-fujin.github.io/	[12]
TBSI/Sanwoda	Lab	NCM811 batteries with a nominal capacity of 1.1 Ah were cycled under 9-step fast charging (0.33C–3C, where 1C is 1.1A) and 1C constant discharging conditions.	Degradation diagnosis	https://github.com/terencetaothucb/TBSI-Sunwoda-Battery-Dataset	[182]
TBSI	Lab	464 retired LIBs, covering 3 cathode types, 6 historical usages, 3 physical formats, and 6 capacity designs.	Degradation diagnosis	https://github.com/terencetaothucb/Pulse-Voltage-Response-Generation	[98]
TUM	Lab	Ageing data from 196 commercial lithium-ion cells cycled under varied calendar and cyclic ageing conditions.	Degradation diagnosis	https://mediatum.ub.tum.de/1713382	[183]

sources, such as the heat contributions from the cell casing and ejected materials, researchers can gain a more accurate understanding of the thermal behavior during TR. Additionally, the high-speed synchrotron radiography videos provide visual insights into the internal dynamic responses of cells under extreme conditions, enabling researchers to analyze the mechanisms behind battery responses in these scenarios.

(2) National Big Data Alliance of New Energy Vehicles

The NDANEV real-world operational dataset, collected through the National Big Data Alliance of New Energy Vehicles, represents one of the most comprehensive NEV datasets in China. As of July 2024, it includes data from over 21 million connected vehicles, covering approximately 90 % of the national NEV fleet, with a cumulative mileage exceeding 890 billion kilometers. The dataset consists of high-frequency time-series records transmitted at intervals of 10–30 s, in compliance with GB/T 32960 [155]. Each record includes 73 standardized items capturing both vehicle-level and battery-level states, such as speed, accumulated mileage, current, voltage, battery temperature, and SOC. This large-scale dataset reflects real-world driving conditions across diverse environments and usage patterns, making it valuable for studying performance degradation, safety risks, and long-term ageing mechanisms. Compared with laboratory data, it offers greater representativeness and enables the development of more generalized diagnostic and prognostic models for batteries under practical conditions.

(3) Big Data Generation Platform

Researchers at RWTH have developed a simulation platform [156] to address the challenge of limited data availability for battery faults. Compared to ageing data, fault data are extremely scarce, yet they play a crucial role in advancing fault diagnosis and safety analysis of LIBs. To overcome this limitation, the platform generates synthetic safety data that closely replicates real-world conditions, supporting the development and validation of data-driven diagnostic methods. It systematically combines electrical, thermal, and ageing models with multiple fault models, including hard SC, soft SC, abnormal IR, and abnormal contact resistance. The platform also accounts for both cell-level and pack-level variations, such as manufacturing differences, temperature gradients, ageing patterns, operating conditions, and fault severity. Through Monte Carlo simulations, it generates large-scale, realistic datasets, providing a valuable resource for early fault prediction and safety risk assessment while reducing the cost and time required for experimental data collection.

(4) XJTU Dataset

The battery test involves 55 lithium-ion 18650 cells manufactured by "LISHEN," featuring a NCM chemistry ($LiNi_{0.5}Co_{0.2}Mn_{0.3}O_2$), with a rated capacity of 2000 mAh and a nominal voltage of 3.6 V. The testing period spans from September 16, 2022, to February 18, 2023, during which six different charge-discharge strategies were applied. By the end of the test, the battery capacity decreased to below 80 % of its initial value. The data were sampled at a frequency of 1 Hz, capturing detailed information about battery performance, degradation and health state. Additionally, preprocessing and health state estimation codes are provided for users to apply or modify the dataset for further analysis. The dataset allows researchers to test and validate ML or DL models for SOH estimation, degradation forecasting and capacity estimation, providing a solid foundation for algorithm development and contributing valuable insights to battery performance evaluation and degradation prediction.

Taken together, the critical role of battery data resources in accelerating energy storage innovation cannot be overstated. Battery data plays a crucial role in battery research, serving as the foundation for understanding battery performance, degradation mechanisms and safety issues. High-quality data not only reveals the behavioral characteristics of batteries under various operating conditions but also provides essential support for modeling and optimization. Therefore, systematically organizing and analyzing various publicly available battery datasets is of great significance. On the one hand, it offers researchers a wealth of data resources, fostering cross-disciplinary collaboration and innovation. On the other hand, standardized data and open sharing help enhance the reproducibility of research, laying a solid foundation for accelerating the development and application of battery technologies.

Hence, we strongly advocate for the global open-source sharing of comprehensive battery datasets that cover the full lifecycle, from early usage to EOL across multiple time scopes. This includes detailed degradation trajectories, fault evolution patterns and TR events under both normal and abusive conditions. In particular, the establishment of joint ageing–TR datasets should be emphasized. While ageing datasets and TR datasets are relatively abundant, there is a notable scarcity of coupled datasets that capture the transition from long-term degradation to sudden failure. Constructing and sharing such integrated datasets would provide a crucial foundation for understanding the ageing–safety nexus and for developing predictive tools that can bridge gradual degradation with catastrophic events. By encouraging the open publication of such rich and diverse data, we aim to empower the research community to develop more robust diagnostic models, accelerate safety-critical innovations and collectively advance the next generation of energy storage technologies.

4. Key challenges and opportunities

We believe that future efforts in battery performance evaluation and safety risk assessment should primarily focus on two key directions: first, achieving a comprehensive full-lifecycle evaluation that bridges battery degradation and safety evolution; and second, developing methods that are scalable and applicable to real-world, large-scale deployment. To this end, we critically examine current limitations in both fundamental understanding and methodological approaches, and propose several practical and meaningful outlooks to guide future research and application.

4.1. Main research gaps

4.1.1. Lab-to-industry limitations in large-scale deployment

Currently, the safety and performance assurance of battery systems in large-scale applications, such as EV fleets and energy storage systems, has become increasingly important. In these contexts, battery degradation diagnosis, fault detection, and TR prediction face heightened requirements. Although research in these areas has advanced significantly, considerable technical and engineering limitations remain when these methods are applied in real-world large-scale deployments. Lab-scale approaches, typically developed under controlled conditions and fixed ageing protocols, may not capture the diverse operating conditions, complex usage behaviors, and variable degradation paths encountered in actual vehicles or storage systems.

From a technical standpoint, most existing degradation prediction and diagnostic models are developed based on small-scale experimental data collected under specific operating conditions. As a result, these models generally lack the generalization ability required to accommodate the wide diversity of battery chemistries, operational environments, and usage behaviors observed in practical applications. In real-world scenarios, fault labels are often missing, and degradation- and safety-related indicators such as capacity or IR measurements are also unavailable in many cases. The absence of key information makes it more difficult to accurately characterize ageing behaviors and train models that are both reliable and interpretable. Moreover, multiple degradation mechanisms, including lithium plating, SEI growth, and gas evolution, can occur simultaneously and interact in complex ways. This interaction complicates the task of isolating and identifying specific fault

modes. As a consequence, current models often suffer from low diagnostic performance, high false alarm rates, and inadequate early warning capabilities, which significantly hinder their practical application in real-world scenarios.

From the perspective of data availability, the lack of high-quality and well-labeled degradation and fault data is a major obstacle to improving diagnostic performance. In real-world applications, data related to rare events such as TR is extremely scarce, leading to serious class imbalance problems in supervised learning approaches. Additionally, the data collected by BMSs is often low-frequency and compressed, lacking crucial transient and localized information that is important for fault detection. Some key health indicators, such as sudden changes in IR or electrolyte decomposition, are also not directly observable with existing sensor technologies. These further compromise both the reliability and interpretability of model-based diagnostics.

In terms of system deployment and maintenance, the computational demands of many advanced diagnostic models limit their real-time implementation on embedded hardware platforms. DL-based models, in particular, require substantial computational resources and energy consumption, which exceed the capabilities of typical in-vehicle systems. Although cloud-based diagnostic frameworks offer enhanced computational power, they introduce concerns regarding data transmission latency and cybersecurity risks. Moreover, diagnostic models often require retraining or recalibration for different battery models or manufacturing batches, resulting in high maintenance costs and making large-scale deployment more challenging.

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From a technical standpoint, most existing degradation prediction and diagnostic models are based on small-scale experimental data collected under specific operating conditions. As a result, these models generally lack the generalization ability required for industrial-scale applications. In practical deployments, capacity labels are often missing because full charge–discharge cycles are rarely performed in real vehicles; measurable parameters are also far fewer than in laboratory environments, making lab-scale methods difficult to apply directly. Moreover, the degradation trajectory of batteries in real-life operation is complex and variable, whereas lab-scale methods are typically constructed based on fixed ageing paths, which limits their generalizability.

Additionally, in real-world scenarios, fault labels and other key health indicators, such as IR measurements, are often unavailable. This absence of crucial information, combined with interactions among multiple degradation mechanisms (including lithium plating, SEI growth, ISC, *etc.*), complicates the isolation and identification of specific fault modes. From the perspective of data availability, the poor quality and sparsely collected degradation and fault data in industrial environments further limit the applicability of lab-derived models. Rare events, low-frequency BMS data, and unobservable key health indicators exacerbate the mismatch between laboratory validation and industrial deployment.

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4.1.2. Coupled mechanisms increase diagnostic complexity

During battery operation, multiple degradation mechanisms often occur simultaneously, including lithium plating, SEI layer growth, gas generation, electrolyte decomposition, and structural changes in electrode materials. These processes are not independent; instead, they can interact with and exacerbate one another in complex, nonlinear ways. For example, lithium plating may accelerate gas evolution, while SEI growth can influence impedance rise and thermal behavior. Such coupling leads to overlapping and non-distinct fault signatures, making it difficult to attribute observed anomalies to specific root causes. This complexity significantly hampers the development of accurate and interpretable diagnostic models, especially in the absence of high-resolution sensing data or well-labeled failure cases.

Moreover, current research on battery safety diagnostics often overlooks the critical influence of ageing effects. Many diagnostic models are developed under fixed or idealized ageing conditions, failing to account for how degradation dynamics evolve over the battery's lifespan. As a result, their performance may degrade when applied to real-world batteries, which may experience diverse usage patterns and progressive ageing. This gap underscores the urgent need for safety diagnostic frameworks that not only detect and isolate faults but also adapt to ageing-related changes in fault manifestations. Therefore, understanding and modeling the interplay among degradation pathways, particularly under different ageing stages, is essential for advancing fault isolation and ensuring reliable health assessment in battery systems.

4.1.3. Challenges in validating and integrating TR prediction models

Current methods for predicting TR in battery systems predominantly rely on electro-thermal simulations or data derived from small-scale laboratory experiments. These approaches often fail to account for the full complexity of real-world operating conditions, including variations in ambient temperature, load profiles, battery degradation, and the diverse behaviors of different battery chemistries. Furthermore, the validation of these models is frequently limited to isolated components or lab-scale setups with minimal real-world testing at the vehicle or large-scale energy storage system level. As a result, these predictive models tend to suffer from high false alarm rates, which occur when the system incorrectly flags normal operating conditions as potential TR events. Additionally, the models often lack the sensitivity required for early warning, which is critical to prevent catastrophic failures before they escalate. The limited capabilities of current sensor technologies further hinder the early identification of TR. Many existing sensors are unable to detect critical early indicators, such as rapid increases in internal temperature or subtle changes in impedance, which are essential for detecting TR in its nascent stages. This combination of false positives, delayed warnings, and sensor limitations restricts the practical deployment of these TR prediction models in large-scale applications such as electric vehicle fleets and energy storage systems, where timely and reliable predictions are essential to ensure safety and prevent damage. To address these shortcomings, future research should focus on enhancing model accuracy through real-world validation, improving the integration of multi-modal sensing data and incorporating advanced ML techniques to reduce false alarms and improve the timeliness of predictions.

4.1.4. Economic and technical hurdles in diagnostic system implementation

Economic and engineering considerations present significant challenges to the widespread adoption of advanced battery diagnostic

solutions. Achieving high diagnostic accuracy or effective early warning capability often requires the integration of additional sensors and advanced data acquisition modules, which in turn increases the overall system complexity and cost. The need for these extra components raises the financial burden, making it difficult for some applications, especially in cost-sensitive industries, to justify the investment. Furthermore, these added complexities can complicate the system's maintenance, as more components mean higher potential for failure or the need for recalibration. Without a well-defined framework for evaluating the economic benefits of these advanced diagnostic solutions, it becomes challenging to establish clear cost-benefit ratios, which limits their appeal for large-scale adoption. In particular, for applications such as EVs and energy storage systems, where cost efficiency is crucial, the high cost of implementation can act as a barrier. Additionally, the absence of unified standards for diagnostics, data formats, and performance metrics further exacerbates the problem. This lack of standardization makes it difficult for different platforms and systems to communicate effectively, thereby hindering cross-system collaboration and reducing the scalability of these diagnostic tools. The fragmentation of standards results in inefficiencies and limits the ability to share vital information, impeding the development of interoperable solutions that could enhance the overall effectiveness of BMSs.

In conclusion, although notable progress has been made in battery degradation diagnosis, fault detection, and TR prediction, substantial challenges remain for their practical deployment at scale. Future efforts should focus on improving model generalization, leveraging unlabeled and real-world field data, enabling lightweight and real-time deployment, developing comprehensive economic assessment frameworks, and establishing standardized diagnostic protocols. In light of the above-mentioned gaps, we outline several practical and promising future directions aimed at enhancing the scalability, reliability and applicability of battery diagnostic systems in real-world settings.

4.2. Outlook

Building upon the aforementioned gaps, future research should explore more integrated and intelligent frameworks to meet the demands of large-scale and real-world applications. Battery digital twins (DTs) technology, which combines multi-physics modeling with real-time data and artificial intelligence (AI), presents a promising solution for continuously updating battery states and enabling more accurate tracking of degradation and fault prognosis throughout the battery lifecycle. In parallel, multi-modal sensing technologies can offer richer and more granular information by integrating thermal, acoustic, mechanical, and electrochemical signals. This enhanced observability can significantly improve the detection of early-stage faults and the understanding of complex degradation interactions. Moreover, the development of large AI models, pre-trained on diverse and extensive battery datasets and subsequently fine-tuned for specific tasks, may greatly enhance generalization, interpretability, and adaptability across different battery chemistries, configurations, and operational conditions. Together, these research directions can help establish scalable, adaptive, and cost-effective solutions for the next generation of BMSs.

4.2.1. Battery digital twin

DT technology is an advanced computational framework that creates a high-fidelity virtual replica of a physical system, enabling real-time synchronization, analysis, and optimization [184]. A DT integrates physics-based models, data-driven approaches, and AI to learn and adapt from real-world operational data continuously. By leverageing multi-source data fusion and predictive analytics, DTs provide deep insights into system behavior, failure mechanisms, and lifecycle performance. Initially developed for aerospace and industrial manufacturing, DT technology has now been widely adopted in complex systems such as energy storage and EVs, where reliability, safety, and efficiency are critical.

In the battery domain, DTs offer transformative capabilities across the entire lifecycle, from material development to system operation [12]. One of the most notable advantages of DT technology is its ability to overcome the limitations of existing diagnostic approaches, which often lack physical interpretability and cannot directly reflect the internal states of batteries. By constructing a physics-informed virtual replica that evolves with real-world data, DTs provide unprecedented visibility into internal degradation mechanisms and state transitions, enabling more accurate, explainable, and proactive diagnostics.

At the material level, DTs accelerate the discovery and optimization of new battery chemistries by simulating electrochemical reactions, degradation pathways, and structural evolution under various operating conditions. At the cell level, DTs enable the precise modeling of battery ageing, thermal behavior, and mechanical stress, facilitating more efficient cell design, manufacturing quality control, and performance validation. At the system level, DTs are integrated into battery BMS to enhance real-time state estimation, fault diagnosis, and predictive maintenance [185]. By continuously updating based on real-world data, DTs help optimize energy management strategies, extend battery lifespan, and improve safety by preemptively identifying risks such as TR. Li et al. [186] innovated a cloud-based BMS leverageing IoT-driven DT technology, where real-time battery data is transmitted to the cloud to construct a virtual replica integrating ECMs for adaptive state estimation. This DT framework employs an extended H-infinity filter for robust SOC estimation and a PSO-optimized algorithm to concurrently track capacity and power fade during ageing, validated through hardware-in-loop prototypes across stationary and mobile scenarios. Guo et al. [187] introduced an electrochemical DT to address the limitations of conventional tools in capturing multiscale ageing mechanisms under fast charging. The DT was constructed as a physics-based virtual replica of the $LiNi_{0.5}Co_{0.2}Mn_{0.3}O_2$/graphite battery system, integrating real-time electrochemical data with post-mortem material characterization to bridge macroscopic performance degradation and microscopic structural/chemical evolution, achieving superiority in quantifying ageing effects. By bridging the gap between physical batteries and their virtual counterparts, DTs are revolutionizing battery research, manufacturing, and operation, paving the way for safer, more reliable, and sustainable energy storage solutions.

Despite the significant progress of battery DT technology in both research and application, its large-scale deployment in real-world systems remains limited due to several challenges. First, the development of DTs depends on the availability of high-quality, multi-source data. However, in practical operational environments, battery data often suffers from low sampling frequency, incompleteness, and a lack of labeling, which restricts the training and validation of models. Second, high-fidelity DT models generally require the integration of complex physics-based modeling and data-driven approaches, resulting in high computational costs that hinder efficient implementation in embedded systems with limited resources. In addition, the wide diversity in battery chemistries, operating conditions, and usage behaviors across different application scenarios presents difficulties in creating universal and transferable DT frameworks.

To promote the broader adoption of DT in battery systems, future efforts should focus on several key areas. First, establishing standardized and shareable multi-scale battery data platforms is crucial for improving data accessibility and quality, which in turn supports the development of robust models. Second, the advancement of lightweight and real-time modeling and inference algorithms is necessary to enable the efficient

deployment of DT models on edge computing devices. Third, the application of techniques such as transfer learning [188] and federated learning can enhance the adaptability and generalization capabilities of DTs, thereby reducing their dependence on specific use cases. Moreover, fostering interdisciplinary collaboration by combining expertise from electrochemistry, materials science, AI, and control engineering will be essential for developing robust, intelligent, and interpretable DT systems for batteries. Such efforts will provide a solid foundation for building intelligent, safe, and sustainable energy storage solutions.

4.2.2. Multimodal sensing technology

Data serves as the most fundamental cornerstone for battery system diagnostics—not only does the quantity of data matter, but its quality is equally critical. Signals collected solely through the BMS, which primarily include voltage, current, and temperature, often suffer from limitations such as low spatial resolution, insufficient sensitivity to early-stage faults, and delayed reflection of internal degradation mechanisms. These limitations can result in untimely or inaccurate estimations and diagnoses, particularly under dynamic or complex operating conditions. To address these challenges, multimodal sensing technology has emerged as a promising solution [189]. It refers to the integration of multiple types of sensors that capture diverse physical, chemical, and mechanical signals from battery systems. Compared with single-modality sensing, multimodal approaches provide a more comprehensive and high-dimensional understanding of battery behavior, which is especially valuable for state estimation, degradation analysis, and early fault detection.

Multimodal sensing technology refers to the integration of multiple types of sensors that capture diverse physical, chemical, and mechanical signals from battery systems. Compared with single-modality sensing, multimodal approaches provide a more comprehensive and high-dimensional understanding of battery behavior, which is especially valuable for state estimation, degradation analysis, and early fault detection [190]. Typical modalities include electrochemical signals (voltage, current), thermal responses (temperature distribution), mechanical stress (strain, expansion), gas release (pressure, gas sensors), acoustic emissions, and optical signals (spectroscopy or imageing). The fusion of these complementary data sources enhances the observability of internal processes such as lithium plating, TR onset, and structural failure.

In recent years, advancements in embedded sensing, flexible electronics, and low-power microsensors have facilitated the deployment of multimodal sensor arrays within or near battery cells. Research has demonstrated that combining thermal and acoustic signals, as we discussed in Section 3.3, can improve the early detection of ISC or thermal anomalies. Similarly, integrating mechanical and electrochemical signals can help characterize cell swelling and correlate it with degradation states. Despite these promising developments, several challenges remain. First, the physical integration of multimodal sensors into battery packs is non-trivial due to constraints on space, thermal insulation, and electrical interference. Second, the fusion of heterogeneous data types with different sampling rates, noise characteristics, and measurement uncertainties requires sophisticated signal processing and data-driven algorithms [191]. Moreover, the lack of standardized test protocols and data labeling schemes hinders model generalization and benchmarking across different battery chemistries and designs. Finally, the increased complexity and cost of multimodal systems can limit their scalability in commercial applications.

To address these challenges, future research should focus on the development of miniaturized, flexible, and robust multimodal sensors that can be seamlessly embedded during battery manufacturing. Progress in edge computing, self-supervised learning, and cross-modal data fusion will enable real-time interpretation and decision-making from rich sensory inputs. Establishing large-scale, annotated datasets from multimodal sensing experiments will further accelerate the training and validation of ML models. Ultimately, multimodal sensing is expected to play a pivotal role in advancing intelligent BMSs, enabling safer, smarter, and more sustainable energy storage technologies.

4.2.3. Large AI models

The emergence of large AI models provides new opportunities for advancing battery management. With their exceptional capacity for representation learning and cross-domain generalization, these models are capable of extracting latent degradation features, identifying early-stage faults, and capturing subtle precursors to thermal hazards from high-dimensional and multimodal battery data. By leverageing pretraining on large-scale datasets and fine-tuning for specific battery tasks, large AI models demonstrate promising potential in enhancing the accuracy and robustness of battery state estimation under varying operating conditions and ageing stages [192].

Currently, the adoption of pretraining and fine-tuning strategies enables large AI models to support integrated prediction frameworks throughout the battery lifecycle. In addition, advances in large-scale modeling have inspired efforts to construct more generalizable battery models that can perform multiple tasks within a single architecture. Such tasks include capacity forecasting, lifetime estimation, fault classification, and safety risk assessment. Feng et al. [193] developed a large language model-based framework for cross-battery SOH estimation, leverageing the generalization ability of large-scale models to map heterogeneous degradation patterns into unified latent representations. During deployment, the model dynamically adapts to distribution shifts through test-time training, continuously refining its parameters using incoming unlabeled battery data streams. This approach achieved state-of-the-art accuracy across 62 batteries by aligning domain-invariant features while preserving chemistry-specific degradation dynamics. Sun et al. [194] proposed a TimeGPT-based framework for LIBs SOH estimation, treating it as a time series prediction task and fine-tuning the foundation model on cycling data from 143 batteries spanning six cathode chemistries. The model dynamically adapts to diverse operating conditions through parameter refinement during fine-tuning, achieving domain transfer by learning shared degradation temporal patterns while preserving chemistry-specific dynamics. Overall, this unified approach improves modeling efficiency and reduces reliance on large volumes of task-specific data.

Despite their promise, the practical application of large AI models faces several challenges. High computational requirements and long inference times raise doubts about whether these models can be effectively deployed within embedded BMSs that have limited resources. Another major challenge is the lack of interpretability, which complicates safety validation and trust in model decisions. Integrating physical knowledge into AI models, such as electrochemical constraints, offers a promising approach to enhance transparency and reliability [195]. Summarily, their widespread adoption will depend on continued advancements in model efficiency, interpretability, data availability, and application-level safety assurance. However, these methods still hold significant application potential, and it is worthwhile for researchers to contribute to exploring how to translate them into practical deployments.

4.3. Summary

To achieve intelligent and durable battery management across the full lifecycle in real-world applications, the integration of advanced technologies such as battery DTs, multimodal sensing, and large AI models, hold significant potential. As illustrated in Fig. 12, these technologies represent promising future directions for advanced BMSs. DTs integrate physics-based simulations with real-time operational data, offering deeper insights into battery performance and enabling more accurate predictive diagnostics. Multimodal sensing captures a diverse set of signals including thermal, mechanical, and electrochemical responses, which improves system observability, supports early fault detection, and enriches the understanding of degradation. Large AI

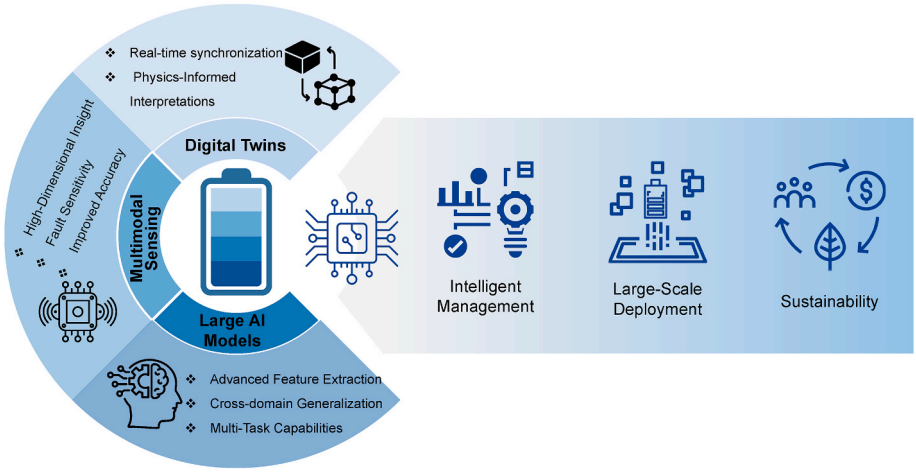


Fig. 12. Future trends for better battery management.

models, trained on extensive and diverse datasets, provide strong generalization and adaptability, enhancing the accuracy of state estimation across various battery chemistries and usage scenarios. The convergence of these technologies would establish a robust framework for smarter, safer, and more responsive battery management. Such an integrated approach not only facilitates large-scale deployment but also promotes economic viability and environmental sustainability, by reducing operational costs, optimizing energy storage efficiency, and supporting a more reliable and safer transition to renewable energy systems.

5. Conclusions

Lithium-ion batteries are central to the electrification of transportation and renewable energy integration, however performance degradation and safety risks pose critical obstacles to their widespread deployment. This review elucidates the crucial link between degradation mechanisms and safety risks, demonstrating how progressive ageing influences fault evolution and thermal runaway hazards—a relationship largely overlooked in prior literature. Building on this, we emphasize advanced diagnostic strategies capable of tracking long-term performance degradation, detecting medium-term faults and short-term thermal runaway, thereby enabling timely interventions to ensure battery reliability. The role of comprehensive data resources, as the foundation for intelligent diagnostics and predictive modeling, is also underscored. Looking ahead, we identify key enablers for next-generation battery diagnostics: deploying of digital twins to simulate degradation-safety coupling, integrating multimodal sensor data to enhance observability, and utilizing large AI models to improve diagnostic generalization and scalability. By bridging the understanding of degradation and safety, this work addresses a fundamental scientific challenge and provides a roadmap for developing intelligent, adaptive energy storage systems capable of meeting the demands of future sustainable energy infrastructures.

CRediT authorship contribution statement

Yiwen Zhao: Writing – original draft, Methodology, Investigation, Conceptualization. **Zhenpo Wang:** Writing – review & editing, Supervision, Conceptualization. **Lisen Yan:** Writing – review & editing, Methodology. **Zhenyu Sun:** Writing – review & editing, Investigation. **Peng Liu:** Writing – review & editing, Investigation, Conceptualization. **Lei Zhang:** Writing – review & editing, Methodology, Funding acquisition. **Weihan Li:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.etran.2025.100497.

Data availability

No data was used for the research described in the article.

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