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Review

Recent Advances in Thermal Management Strategies for Lithium-Ion Batteries: A Comprehensive Review

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Abstract: Effective thermal management is essential for ensuring the safety, performance, and longevity of lithium-ion batteries across diverse applications, from electric vehicles to energy storage systems. This paper presents a thorough review of thermal management strategies, emphasizing recent advancements and future prospects. The analysis begins with an evaluation of industry-standard practices and their limitations, followed by a detailed examination of single-phase and multi-phase cooling approaches. Successful implementations and challenges are discussed through relevant examples. The exploration extends to innovative materials and structures that augment thermal efficiency, along with advanced sensors and thermal control systems for real-time monitoring. The paper addresses strategies for mitigating the risks of overheating and propagation. Furthermore, it highlights the significance of advanced models and numerical simulations in comprehending long-term thermal degradation. The integration of machine learning algorithms is explored to enhance precision in detecting and predicting thermal issues. The review concludes with an analysis of challenges and solutions in thermal management under extreme conditions, including ultra-fast charging and low temperatures. In summary, this comprehensive review offers insights into current and future strategies for lithium-ion battery thermal management, with a dedicated focus on improving the safety, performance, and durability of these vital energy sources.

Keywords: thermal management strategies; lithium-ion batteries; extreme conditions thermal management; advanced sensors; machine learning algorithms

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1. Introduction

In the current landscape of sustainable mobility, the thermal management of lithium-ion batteries (LIBs) in electric vehicles (EVs) has established itself as an essential field of research, crucial to improving the efficiency and ensuring the safety of these energy systems. Battery thermal management systems (BTMSs) play a key role in this context, as they are decisive in keeping LIBs within an optimal temperature range, thus contributing to optimizing their performance and prolonging their lifetime. Recent research [1] highlights that advances in innovative materials and advanced designs in BTMSs are key for the effective management of the heat generated in the charging and discharging processes, which is especially relevant in high-demand applications such as EVs. However, the field faces significant challenges, mainly related to overheating and temperature variations in LIBs. These problems can compromise both the safety and performance of batteries, accelerating their aging and reducing their energy storage capacity. In extreme cases, these problems can even trigger fire or explosion risks due to thermal runaway (TR) [2]. This situation underlines the imperative need for efficient BTMSs that mitigate these risks, maintaining uniformity in battery temperature and avoiding extreme conditions [3,4]. Studies such as those presented in [5] emphasize the critical importance of integrity in BTMS studies, focusing on battery thermal safety as a key element to prevent overheating-related incidents in advanced battery technologies.

Advances in BTMSs have shown significant benefits in EVs, providing more accurate and uniform temperature regulation, and resulting in improved battery efficiency and reliability. Innovations in phase change materials (PCMs) and other BTMS technologies have improved heat dissipation and TR prevention, increasing the safety and energy density of batteries [1]. The study of heat generation in LIBs has gained importance, particularly in its impact on battery performance and safety. Scholars [6,7] have focused on understanding the interplay between thermo-electrochemical processes within batteries and how variable battery properties affect heat generation internally. Additionally, there has been a notable focus on developing effective thermal management strategies for use in EVs, with innovative methods combining pulsed operations with external liquid circulation, air and liquid cooling, PCMs, and heat pipes, each with its advantages and disadvantages [8–10]. Recently, a hybrid system has been highlighted that combines liquid cooling channels with PCMs, optimizing thermal efficiency and minimizing pressure loss [11]. Despite significant progress in the literature on the thermal management of lithium-ion batteries, critical challenges persist, warranting further in-depth investigation. The optimization of battery efficiency and safety remains a dynamically evolving area of study, given the rapid growth of technologies such as EVs and escalating demands for battery performance and durability. Identifying gaps in the literature underscores the necessity to address specific issues, including managing internal heat generation and implementing practical thermal management strategies in real-world scenarios. Despite advancements, there are still limitations in understanding how the variable properties of batteries impact heat generation and how these issues influence the long-term integrity and safety of batteries in high-demand applications. In this context, this work focuses on filling these gaps in the literature, presenting not only a comprehensive review of current advancements but also proposing innovative contributions that address these specific challenges. The key contributions of this study are summarized as follows:

- The primary contribution of this work lies in its comprehensive approach, addressing not only thermal efficiency to enhance battery performance but also placing significant emphasis on safety. This is achieved through innovative strategies in the design of BTMSs that tackle both overheating and temperature variations, thereby mitigating risks of accelerated aging and potential fire hazards.
- We contribute to the scientific literature by highlighting the essential role of advanced materials and innovative designs in BTMSs. This work provides a thorough review of recent advancements in this regard, emphasizing how these innovations can be crucial for effective thermal management during charging and discharging processes, especially in high-demand applications such as electric vehicles.
- A significant novelty of this review is the emphasis on researching internal heat generation in lithium-ion batteries. Through a detailed analysis of thermo-electrochemical processes and the impact of variable battery properties on heat generation, this work contributes to a better understanding of the fundamentals underlying battery efficiency and safety.
- This paper highlights a comprehensive evaluation of various thermal management strategies used in EVs. From pulsed operations to hybrid systems combining liquid cooling with PCMs, we provide a complete overview of the advantages and disadvantages of each approach, identifying best practices to optimize thermal efficiency and minimize pressure loss.
- We present specific results from a recent hybrid system that combines liquid cooling channels with PCMs. This work not only highlights the theory behind this innovation but also demonstrates its practical application, optimizing thermal efficiency and addressing pressure loss, which is crucial for successful implementation in EVs.

The rest of this study is structured as follows: Section 2 delves into the fundamentals of thermal management of LIBs and the shortcomings of existing systems. Section 3 focuses on advances in cooling methods, while Section 4 discusses sophisticated thermal management models. Section 5, meanwhile, investigates novel technologies in thermal monitoring and regulation. The aim is to highlight the critical role of BTMSs in the sustainable development of EVs and to make valuable contributions to the field of thermal management research, presenting findings relevant to both specialists and researchers in related fields. Finally, Section 6 concludes the paper.

2. Thermal Management in Lithium-Ion Batteries

Thermal management in LIBs is critical to their efficient and safe operation, especially in applications such as EVs and energy storage systems. Maintaining these batteries within an optimal temperature range, typically between 20 °C and 40 °C, is essential to prevent reliability problems [12,13]. There are three types of approaches to thermal management, active, passive, and hybrid systems, each with distinctive characteristics and suitable for different applications and requirements [14]. Active systems employ mechanical or electrical means, such as pumps and fans, to regulate the temperature of the batteries [15,16]. These methods, which include air and liquid cooling, are highly effective in dissipating heat but have the disadvantage of increasing system power consumption and thus reducing the overall efficiency of the battery [17]. Despite their effectiveness, these systems require a more complex design and are usually more expensive [18].

Passive systems, which use technologies such as PCMs and heat pipes, rely on natural processes such as conduction and convection for heat transfer [19]. These methods do not require additional energy, which makes them more efficient in terms of energy consumption and simpler in design. However, they may face challenges in their ability to handle high thermal loads or in situations of extreme temperatures [20]. In addition, certain materials such as PCMs may have issues with low thermal conductivity and risk of leakage after melting [21]. Hybrid systems, which combine aspects of active and passive approaches, seek to balance the advantages of both. For example, the integration of PCMs with air or liquid cooling systems can improve temperature control compared to purely passive methods, without reaching the high energy consumption of fully active systems [22]. These hybrid systems offer a promising solution but require careful design and advanced engineering to achieve an optimal balance between energy efficiency and thermal management effectiveness [23]. The proper choice of thermal management system is essential for LIBs, considering factors such as battery size, lifespan, and charge and discharge rates. Advances in new materials, such as nanometer PCMs, and advanced cooling and heating techniques are improving the efficiency and safety of these systems. These innovations are contributing to the increased adoption of batteries in a variety of applications, reducing costs and encouraging the use of cleaner, more sustainable energies [12]. In addition, the integration and compatibility of these systems with the overall EV or storage system design is a challenge [24]. Numerous research studies have been conducted that have proposed various design improvements to increase the efficiency of BTMSs, as detailed in Table 1.

Table 1. Thermal management systems in batteries: comparative analysis.

Ref.	BTMS Method	Operating Principle	Key Findings	Advantages	Disadvantages
[24]	Active	Uses forced air flow to cool the batteries in a rectangular container.	Modifications to outlet size and shape significantly decrease system temperature, improves cooling uniformity.	Requires no moving parts, improves temperature uniformity.	Limited heat transfer capacity, less effective for high thermal loads.
[25]	Active	Circulates water around the battery pack to dissipate heat.	More effective for thermal management at low cycling rates.	Effective for thermal management at low cycling rates, improves thermal performance.	Not as effective at high cycling rates, may require combination with other systems.

Table 1. *Cont.*

Ref.	BTMS Method	Operating Principle	Key Findings	Advantages	Disadvantages
[26]	Passive	Uses PCMs with applied pressure to enhance heat dissipation.	PCMs show the most promising performance compared to traditional active air/liquid cooling methods.	Maintains stable temperatures without energy consumption, improved performance with pressure.	Increased mechanical complexity and costs due to pressure application.
[27]	Passive	Uses PCMs, such as paraffin, to absorb and release heat during phase change.	Provides more uniform temperature distribution compared to air-cooling and liquid cooling.	Effective thermal management, uniform temperature distribution, paraffin is resistant and safe.	Low thermal conductivity of paraffin, slow thermal response.
[28]	Passive	Proposes a passive BTMS using a tetrahedral lattice porous plate for drone batteries.	Significant reduction in maximum temperature and thermal deviation on the battery surface.	Lightweight, requires no additional equipment, mechanically protects the battery.	Minimal weight increase, challenges in heat management across different operation modes.
[29]	Passive	Based on using PCMs to control temperature through heat absorption and release.	PCM-based BTMSs stand out for their cost-effectiveness and ability to maintain temperature uniformity.	Cost-effective, simple installation, minimal space required, excellent temperature uniformity.	Challenges in PCM application, such as low thermal conductivity and rigidity.
[30]	Hybrid	It combines the high heat absorption of PCMs with the active and localized cooling of thermoelectric coolers (TECs).	Delayed TEC current after PCM reaches 80% melting improves temperature uniformity and energy efficiency.	Improved temperature control, utilizes latent heat of PCMs, active cooling of TEC.	More complex than passive systems, higher cost, TEC requires energy, potential temperature variation.
[31]	Hybrid	Uses active liquid cooling combined with passive cooling materials like PCMs.	Effectively prevents TR propagation; maintains uniform temperature during normal operation.	Effective against TR propagation, maintains thermal uniformity, combines active and passive.	Increased complexity and potential additional costs compared to single systems.
[32]	Hybrid	Integrates liquid cooling systems with passive systems for optimal thermal management.	Considered more viable for future thermal management; effectively cools high-energy/power battery packs.	Combines the advantages of active and passive systems, enhancing overall thermal management.	More complex and expensive than single cooling systems.
[33]	Hybrid	Combination of PCMs with active cooling methods for effective thermal management.	Highlights benefits of integrated solutions, needs further research for higher conductivity PCMs.	Improves thermal uniformity and performance, optimizes temperature.	Challenges in integration, need for high conductivity PCMs, environmental impact of larger PCM volume.
[34]	Hybrid	Uses different techniques like air, liquid, and PCMs to cool batteries.	PCM-RT35 showed the best temperature control ability at ambient temperatures of 20 °C or 30 °C.	PCMs offer a passive approach with high efficiency, good temperature management.	PCMs have limited heat absorption capacity, complexity in managing multiple systems.

Notable challenges are identified in BTMSs, especially under harsh operating conditions. A key limitation lies in the low thermal conductivity of PCMs, which leads to uneven temperature distribution within the battery cells, adversely affecting the performance and efficiency of LIBs [33]. This problem is intensified in extreme situations, such as discharge rates higher than 1 °C or in environments with ambient temperatures higher than 35 °C, where temperature differences of less than 3 °C can be observed between individual cells, significantly impacting the performance and durability of LIBs [35]. Also, substantial limitations are observed in current BTMSs, particularly in fast-loading scenarios and high ambient temperatures, which can result in inefficient thermal management and increase the risk of TR [36]. In addition, air-cooled and passive cooling systems show a limited ability to adapt quickly to variations in thermal load, highlighting the importance of developing more dynamic and adaptive BTMSs to improve battery thermal stability over a wider range of operating conditions [37]. This situation is further complicated by the inadequacy of air-cooled and PCM-based systems in contexts of high ambient temperatures or high charge/discharge rates, where the poor thermal conductivity of these systems compromises the long-term performance of the batteries [38].

3. Innovations in Cooling Approaches for Battery Management Systems

Advances in refrigeration techniques, both single-phase and multiphase, have been significant. Single-phase refrigeration, although simpler in design, faces limitations in its heat transfer capacity compared to multiphase techniques [39,40]. Furthermore, one must not only understand the differences in their effectiveness and where they can be best applied, but also consider how improvements in materials, system design, and implementation strategies can help overcome current obstacles. For example, in single-phase cooling, new nanofluids are being explored as a possible solution to improve thermal conductivity and make heat transfer more efficient. Several studies have examined nanofluids with different combinations of base fluids (such as water, ethylene glycol, and engine oil) and nanoparticles (such as alumina (Al_2O_3), iron oxide (Fe_2O_3), copper oxide (CuO), and titanium dioxide (TiO_2)). Although the potential of engine oil nanofluids with Fe_2O_3 has not yet been fully investigated, a significant improvement in the cooling of the battery model has been observed by increasing the Fe_2O_3 concentration from 2% to 5%, which resulted in a decrease in its temperature. The inclusion of Fe_2O_3 as a nanoparticle not only increased the thermal capacity and heat transfer efficiency but also improved the overall thermal performance of the system compared to using engine oil alone [38].

Another nanofluid containing multi-walled carbon nanotubes (MWCNTs) has also shown promise due to its high thermal conductivity and low density. The thermal uniformity of the battery improves with the use of nanofluids, especially at higher MWCNT concentrations. The maximum thermal deviation drops significantly using the 0.45–0.5% MWCNT nanofluid. Another innovative design is the immersion cooling system, which uses a singular fluid in a static state (Novec-7200) and indicates remarkable efficiency in thermal regulation. This system keeps the maximum cell temperature below 40 °C and ensures that the temperature gradient is maintained within a range of 3 °C [39]. Within the field of multiphase refrigeration, traditional refrigerants such as HFCs (hydrofluorocarbons) and HCFCs (hydrochlorofluorocarbons) are two groups of widely used gases that play a crucial role in refrigeration, proving to be vital for efficient performance in environments with extreme temperatures. However, despite being fundamental components in air-conditioning systems, their effect on the environment has prompted the search for more sustainable options [40].

Therefore, new dielectric fluids with lower boiling points are being explored that promise significant improvements in thermal management under various operating conditions. Among these innovative solutions, the use of fluids such as SF33 stands out for their ability to maintain battery temperatures below 34 °C, representing a notable advance toward more sustainable and efficient cooling practices [41]. In addition, mini-channel cold plate cooling systems containing a two-phase fluid are effective in extracting heat through boiling [42]. The use of specific refrigerants, such as R410a, R134a, and R600a, in direct contact with the battery cells allows a significant improvement in temperature distribution. For example, the use of R600a has achieved impressive heat transfer coefficients, keeping module temperatures within safe and much lower ranges compared to systems without refrigeration [43]. To extend battery lifespan and improve battery safety by effectively optimizing the cooling design, the incorporation of thermal management models becomes indispensable. Further research highlights that choosing the right cooling fluids can markedly increase thermal efficiency, underscoring the vital importance of these models in improving cooling systems [44]. For example, in [45], the authors propose a multi-scale and multiphase model, pioneering in comprehensively simulating the venting process in LIBs during a TR event, from heat and gas generation to particle accumulation. In [46], the authors comment on the NTGK (extreme temperature condition, Tiedemann-Gu-Kim) model, which stands out for its accuracy in simulating the internal electrochemical processes of the batteries, offering realistic results that have been confirmed experimentally, differentiating it from more basic models. Two-phase immersion cooling is the model studied in [47]. This model uses the phase change of the coolant to achieve efficient heat transfer, offering rapid cooling, thermal stability, and energy efficiency, ideal for critical systems such as EV batteries, and maintains the battery temperature below 34 °C.

Another approach analyzed is the pseudo-two-dimensional (P2D) model, which reduces the complexity of the lateral structure in LIBs by focusing on electrode thickness to study ion diffusion and electrochemical dynamics. This method allows an accurate representation of variations in concentrations and electric potentials. Although it is fundamental to understand in detail the behavior of batteries, the intensity of the computational calculations required limits its implementation in instantaneous simulations required by battery management systems [48]. According to other research [39], the electrochemical-thermal model (ECT) is the most complete model for simulating batteries, but its high computational demand limits its practical use. The electrical–thermal (ET) model is preferred in thermal management because of its cost efficiency and accuracy. For thermal degradation studies, the Arrhenius method is used. Equivalent circuit models are valued for their effective approximation of electrochemical behavior with low computational cost. However, thermal management focuses on two strategies for temperature estimation: the first involves the use of artificial intelligence (AI), especially neural networks, and the second relies on models describing the internal electrochemical dynamics. These strategies allow the temperature of batteries to be predicted with high accuracy using power control modules. Artificial neural networks (ANNs), trained with real or simulated data, offer estimates with a minimum error of 1.38% compared to conventional methods, eliminating the need for complex simulations, and positioning itself as an effective tool in thermal optimization [39,40]. Figure 1 shows several types of ANN that can be used to predict battery temperature.

Within these types, Elman-NN networks are suitable to simulate the dynamic thermal behavior of the battery, where the temperature at each instant depends on the previous values. Elman-NNs analyze the variables of mathematical models using hidden layers and a contextual layer, learning the relationship between inputs and outputs with training data [40]. In contrast, LSTMs are key to predicting battery temperature by processing data sequences and addressing thermal complexities. Deep neural networks (DNNs) analyze complex data to predict thermal changes, while convolutional neural networks (CNNs) specialize in detecting and predicting areas of heat from visual data. This set of technologies offers an accurate and advanced solution for efficient thermal management of batteries [41]. The multilayer perceptron (MLP) network is effective in modeling nonlinear interactions, making it ideally suited to address challenges in thermal problems that feature nonlinear physical complexities. It uses meaningful inputs such as heat generation and temperature measurements, providing a rich contextual basis for analysis. MLP excels at predicting temperatures with a margin of error of only 0.8 °C using a single sensor, demonstrating its high efficiency in data-constrained contexts [42].

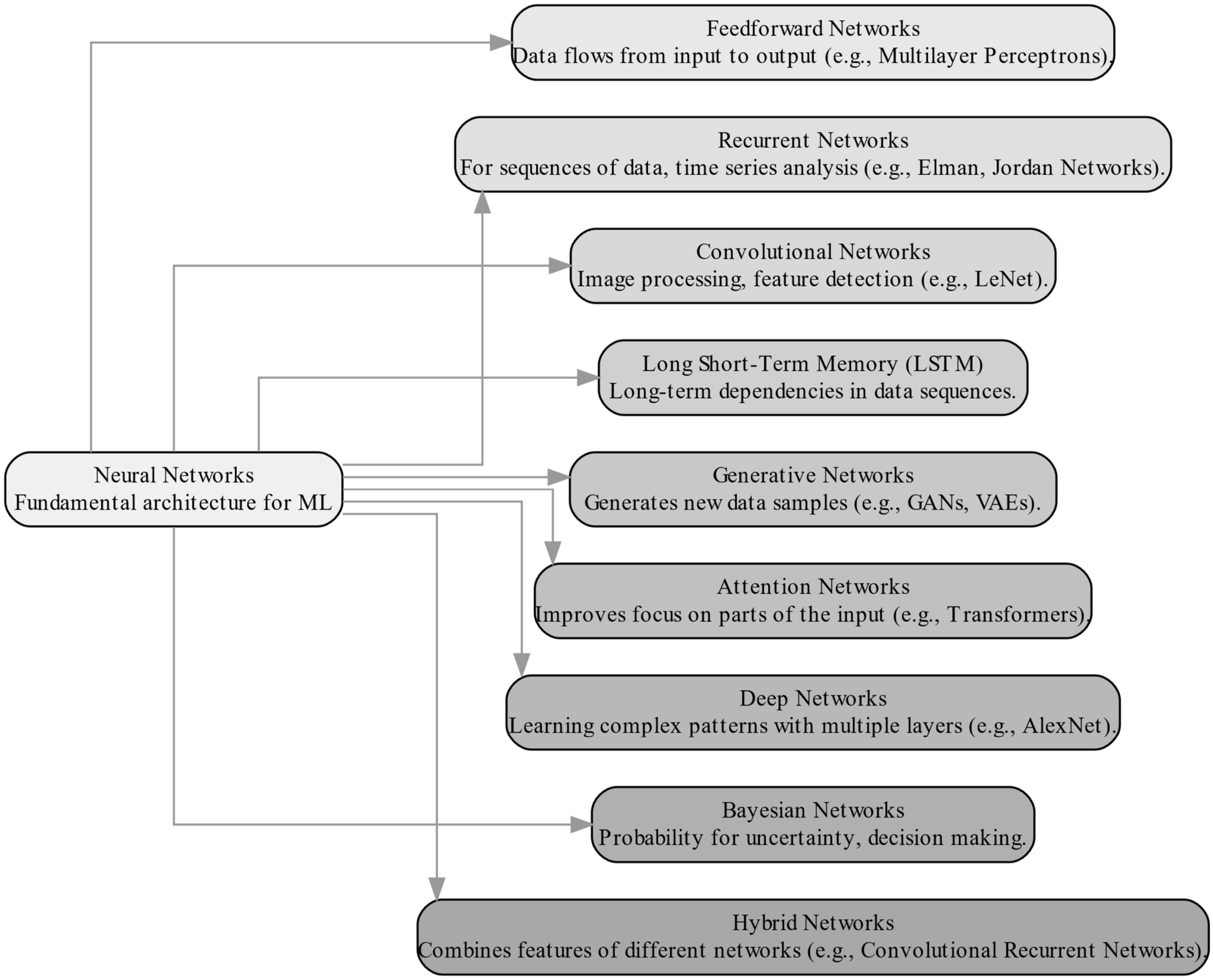

Figure 1. Core structure of machine learning (ML) systems.

On the other hand, model-based approaches delve into the internal reactions and properties to simulate their behavior and battery wear using tools such as the Kalman filter (KF), extended Kalman filter (EKF), unscented Kalman filter (UKF), and particle filtering (PF), among others. These methods seek to pinpoint internal conditions, e.g., load level. Hybrid models, which combine several techniques, are particularly effective. However, challenges, such as accuracy in the representation of deterioration and parameter calibration with limited data, remain complex areas [43]. The KF optimizes estimates of noisy dynamical systems by a recursive process that minimizes the prediction error. It is versatile for linear and nonlinear systems, with its effectiveness depending on the accuracy of the model and noise analysis [44]. There are studies in the literature that address this issue. In [45], the authors perform a comparison between the KF, EKF, and UKF for estimating the battery state of charge. They demonstrated that the UKF was the most accurate with an error of less than 0.3%, outperforming the EKF, which reduced the error to less than 0.5% by accounting for nonlinearities, and the KF, which had an error reduced from 2% to 1.5%. The success of the UKF is due to its effective handling of nonlinearities across sampling points, highlighting its superiority in the accuracy of SOC estimation in lithium-ion batteries. The authors of [46] employed the EKF together with a simple resistance–capacitance (1-RC) model that facilitated the determination of the state of charge (SOC) in batteries. This technique proved to be effective in estimating the overall SOC with an error margin of less than 2%. However, it failed to identify specific variations between individual cells, resulting in notable discrepancies between them. This situation points to the need to dynamically adapt and optimize the model for each cell to obtain an individualized and accurate SOC estimation. The authors of [47] use PF for SOC estimation in batteries by an innovative approach using weighted particles to represent possible states. This method simplifies nonlinear calculations, optimizes performance, and employs the radial simplex sphere principle for efficient sampling, achieving more accurate SOC predictions and corrections.

Therefore, the application of the EKF as an essential component of the algorithm designed for real-time estimation of SOC in LIBs of EVs is validated. Therefore, the prediction and measurement functions for applying the battery model within the EKF are described. The estimation process involves estimating the SOC and battery bias voltage in advance, applying a discrete model that incorporates both prior state and recent inputs, and adding a random error component to reflect uncertainty. Parallel to this, the measurement function bridges the current voltage and current observations to the theoretical battery state, adapting to the nonlinear complexity of the battery model and introducing a random error into the measurements. The KF comes into play by continuously adjusting these initial estimates based on the observed differences between predictions and actual measurements, which effectively refines the accuracy of the battery state estimation [48]. Recent innovations in materials and structures are revolutionizing thermal efficiency, especially in the field of LIBs, a key technology in sectors such as EVs. One of the main innovations is the use of PCMs, which keep the temperature of batteries within a safe and constant range by harnessing the latent heat during their phase transitions [35,49,50]. However, these materials often present the challenge of low thermal conductivity, which is being addressed by incorporating high-conductivity metal matrices and adding metal nanoparticles or porous materials [48,49].

Another area of significant advancement is the development of miniature channel cooling plates, which have been shown to be effective in managing battery pack temperature [51,52]. These plates, often made of aluminum, allow for better heat distribution and more effective temperature control. However, they face challenges related to the complexity and cost of production [51]. Hybrid structures combining passive thermal management and active cooling systems have also emerged as promising solutions, offering greater efficiency, but at the cost of increased weight and complexity. In addition, the use of innovative materials such as graphene has been explored to improve heat dissipation due to their high thermal conductivity [49,53]. Advances in the design of airflow structures and the use of fins on cooling plates have also shown improvements in thermal efficiency [52,54]. However, these solutions may increase airflow resistance and require higher energy consumption. One of the most significant advantages of these innovations is their ability to improve the safety and efficiency of batteries, which is critical in high-demand applications such as EVs [55,56]. However, these technologies still face significant challenges, including the trade-off between improvements in thermal conductivity and production cost, as well as the need to effectively integrate these solutions into large-scale battery designs [50,57]. Although significant progress has been made in improving thermal efficiency through various innovations in materials and structures, challenges remain. These include cost optimization, simplification of manufacturing processes, and effective integration of these solutions into large-scale battery systems. Continued research and development are key to addressing these challenges and taking full advantage of the benefits of these advanced technologies. A summary of innovations in battery thermal management is presented in Table 2.

Table 2. Innovations in Thermal Efficiency.

Ref.	Innovations in Thermal Efficiency	Advantages	Disadvantages	Challenges
[35]	Use of PCMs	They absorb latent heat during phase transition, keeping the battery temperature within a safe range.	Low thermal conductivity, which limits the ability to dissipate heat evenly.	Development of materials with higher thermal conductivity and life cycle.
[51]	Use of miniature channel cooling plates	Increased contact area between the coolant and the cells, which improves heat transfer.	Higher complexity and manufacturing cost.	Optimize channel distribution to reduce pressure loss.
[49]	Phase change composite materials	They combine the advantages of PCMs with those of conductive materials, improving thermal conductivity.	Higher production cost.	Develop composite materials with higher energy density.
[55]	Hybrid system combining heat pipes with evaporative cooling	Improves thermal efficiency in high-current applications.	Increased complexity and manufacturing cost.	Optimize system design to reduce pressure losses.
[58]	Graphene composite structures	Excellent thermal conductivity, which improves heat distribution within the battery.	High production cost.	Develop more efficient production methods.
[56]	Miniature channel design with tilt angles	Reduces pressure losses, improving heat transfer.	Excessively high tilt angles can cause leakage problems.	Optimize the tilt angle for maximum thermal efficiency.
[50]	Passive interfacial thermal regulator based on shape memory alloy	It changes its thermal conductance reversibly, improving battery performance in hot and cold climates.	Challenges related to the development of shape memory alloys with increased thermal cycling and long-term stability.	Optimize device design to facilitate integration into modules and battery packs.
[59]	Hybrid system combining heat pipes with evaporative cooling	Improves thermal efficiency in high-current applications.	Increased complexity and manufacturing cost.	Optimize system design to reduce pressure losses.
[53]	Modular cooling plate design	Greater versatility and adaptability to variable configurations.	Modular designs require joints and connections that can increase the overall thermal resistance.	Achieve large-scale manufacturing of these modular systems in a cost-effective manner.
[57]	System based on liquid cooling of honeycomb structure and phase-change materials	Significantly reduces the maximum temperature and temperature difference in the batteries.	Structural and cooling complexity leads to higher manufacturing costs.	Evaluation under extreme conditions such as actual loading and unloading cycles or thermal packaging situations.
[60]	Modular liquid cooling system	Greater versatility and adaptability to variable configurations.	Modular designs require joints and connections that can increase the overall thermal resistance.	Achieve large-scale manufacturing of these modular systems in a cost-effective manner.
[61]	System based on liquid cooling of honeycomb structure and phase-change materials	Significantly reduces the maximum temperature and temperature difference in the batteries.	Compact structure and uniform heat dissipation.	Evaluate its performance under extreme conditions such as real loading and unloading cycles or thermal packaging situations.

Table 2. *Cont.*

Ref.	Innovations in Thermal Efficiency	Advantages	Disadvantages	Challenges
[54]	Phase change composite materials	Improve thermal uniformity within the battery modules.	Composite materials tend to be more expensive to produce.	Develop composite materials with higher effective thermal conductivity.
[52]	Mini-channel cooling plates with spine-shaped fins	They improve heat transfer performance and reduce thermal gradients.	Horizontal fins cause a significantly higher pressure loss.	Optimize the geometry and arrangement of the fins to achieve the optimum balance between heat transfer and pressure loss.

4. Emerging Technologies in Thermal Monitoring and Control

In recent years, the growing demand for EVs and energy storage systems has driven intense research and development in the field of lithium-ion batteries. A key aspect of this technological evolution is the efficient and safe management of battery temperature, a complex challenge that involves the fusion of advanced sensors, control systems, and risk mitigation, as well as the application of smart technologies and machine learning. The importance of advanced sensors in this area cannot be underestimated. With the incorporation of distributed optical fibers and nanosensors in battery cells, thermal monitoring with high spatial and temporal resolution has been achieved. These sensors provide critical data that are essential to understanding and managing the internal conditions of batteries, enabling the detection of significant temperature variations that could lead to failures [50,62]. In parallel, control systems have significantly evolved thanks to the integration of AI and ML algorithms. These systems not only process the data collected by advanced sensors but also learn from them, continuously improving their ability to predict and mitigate risks. For example, by analyzing thermal behavior patterns, these systems can anticipate and prevent TR incidents, one of the main risks in LIBs [63]. Risk mitigation is enhanced by the development of intelligent technologies and ML. These tools offer an unprecedented ability to analyze and predict battery behavior, enabling more efficient and safer thermal management. The integration of predictive models based on historical data and techniques such as ANNs and reinforcement learning have resulted in more advanced and reliable battery management systems [64,65]. In short, the convergence of these innovative technologies is transforming the way LIBs are monitored, controlled, and safely maintained. This advancement is not only crucial to improve the efficiency and lifetime of these batteries, but also to ensure their safe use in critical applications such as EVs and large-scale energy storage systems [66,67].

4.1. Advanced Sensors

In the field of LIBs, the incorporation of advanced sensors is revolutionizing the way safety and efficiency are monitored and improved. Thin-film RTD (TFRTD) sensors, specifically copper–nickel alloy sensors, have been noted for their ability to be integrated into current collectors, providing fast and accurate internal temperature measurement. These sensors exhibit 82% faster response speeds and 33% higher accuracy compared to external RTDs, which is crucial to avoid overheating and TR [68]. In external short-circuit detection, non-contact magnetoelectric composite sensors, which combine piezoelectric elastomers and magnetostrictive ferrite, have shown high current sensitivity, with an accuracy greater than 99% and a current sensitivity of 0.346–5.975 mV/A. These sensors can distinguish between short circuits and mechanical vibrations, which makes them suitable for applications in EVs [69]. On the other hand, OFDR-based fiber optic sensors offer distributed temperature measurements with a spatial resolution of up to 3 mm. These sensors can identify heat accumulations around positive current tabs during high-rate discharges, revealing non-uniform heat generations even in small cylindrical cells [70]. In smart batteries, the fusion of multiple internal sensors provides a more accurate way to estimate the SOC. For example, expansion force (EF) sensors have been shown to have a more sensitive relationship with SOC compared to voltage and are independent of dynamic current. These sensors can also provide information on battery health status [71].

FBG sensors are noted for their low invasiveness and resistance to electromagnetic interference, with a temperature sensitivity of approximately 10 pm/°C and strain sensitivity of 1–2 pm/$\mu\varepsilon$. They are capable of quasi-distributed sensing and thermal mapping within battery packs, making them suitable for estimating the state of charge and state of health, and predicting battery capacity [72]. Finally, fiber optic sensors have been used to monitor strain and temperature variations in individual cells, employing algorithms such as the fast-recursive algorithm to establish nonlinear correlation models between strain signals and key electrical parameters, allowing accurate estimation of the SOC in battery packs [73]. These advances represent major progress in the monitoring and management of lithium-ion batteries, paving the way for safer and more efficient applications, especially in EVs and large-scale energy storage systems. Figure 2 shows the classification of advanced sensors in BTMSs.

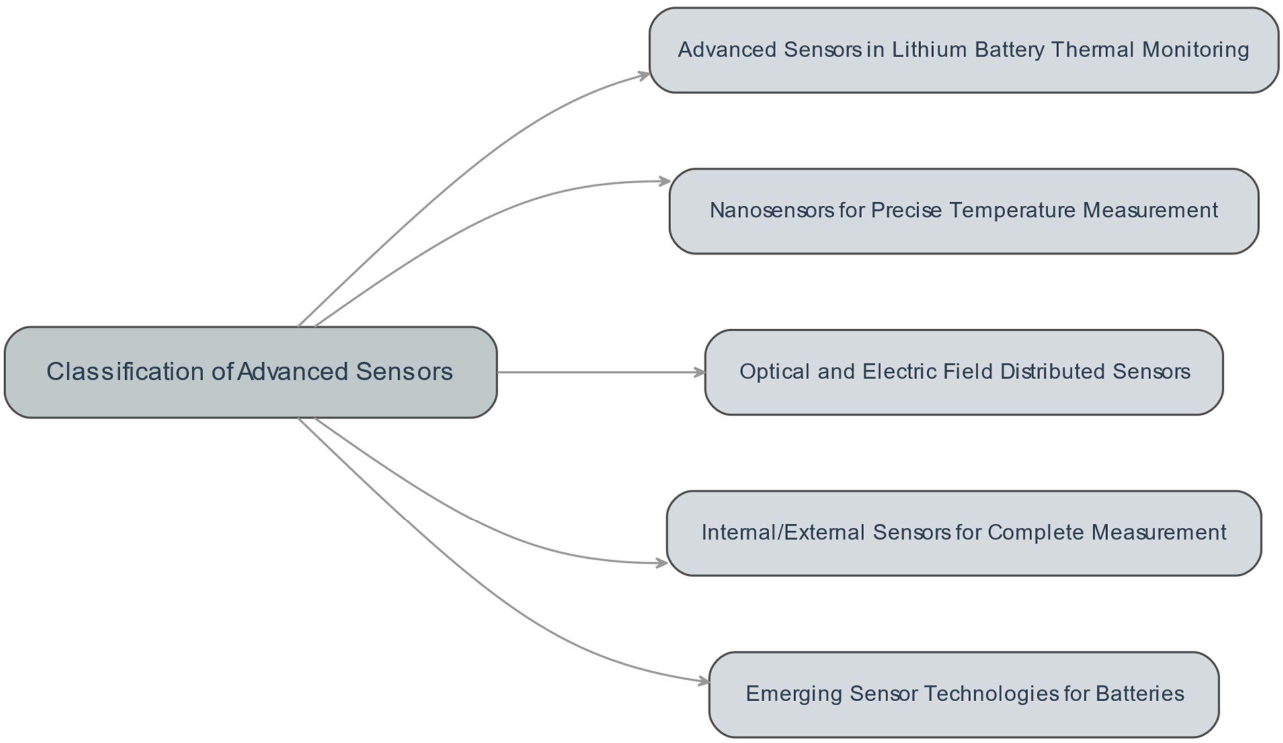

Figure 2. Classification of advanced sensors.

At the heart of this evolution are advanced sensors, whose development continues apace. Emerging technologies such as distributed optical fiber sensors, electric field sensors, and nanosensors offer high spatial and temporal resolution, facilitating detailed thermal mapping of batteries. Particularly, nanosensor-based sensors, composed of materials such as metal oxides and carbon, are capable of measuring temperature in a distributed manner throughout the battery module. Their small size does not affect battery performance and they provide real-time thermal data with high spatial resolution, which is key in smart thermal management [50]. In addition, the use of optical fibers distributed internally in the battery cells allows real-time monitoring of thermal distribution, a significant improvement over conventional sensors. This is vital for detecting temperature variations within the battery and along its length, preventing failures due to temperature differences [62]. The integration of these optical sensors with electric/magnetic field sensors facilitates detailed thermal mapping and allows the detection of variations associated with thermal changes. These dense arrays of sensors collect large volumes of data, essential for accurate and efficient monitoring. Finally, battery monitoring systems include distributed networks of multiple sensors that evaluate thermal and electrical parameters at the cell, module, and pack level, providing a complete picture of the battery status and enhancing the safety and efficiency of battery use [66].

4.2. Application of Intelligent Technologies and Machine Learning

The application of intelligent technologies and ML in battery and power distribution systems has emerged as a critical field in the evolution toward more efficient and safer energy management. In the context of fast charging of lithium-ion batteries, the development of the MSCC-DRL (multi-stage constant current based on deep reinforcement learning) model, which uses deep reinforcement learning, demonstrates a significant advance in reducing charging times while maintaining safety and minimizing battery degradation. In parallel, a systematic review of ML applications in smart distribution systems highlights how these technologies are revolutionizing the planning and operation of power grids, improving the efficiency and effectiveness of these systems [74,75]. In the EV arena, battery technologies and battery management systems have seen remarkable advances. Developments in ANNs for the health management of lithium-ion energy storage batteries, as well as hybrid ML models for thermal modeling and battery diagnostics, are clear examples of how ML is improving the safety, efficiency, and durability of these batteries [76–79]. In addition, the use of deep learning to estimate the state of charge, health, and remaining life of batteries indicates significant progress in intelligent battery management, enabling more accurate and safer operation of battery systems in EVs [79]. The integration of ML models into BMSs has significantly transformed lithium-ion battery management, especially in the context of EVs. The innovative approach presented in [74] illustrates the application of deep reinforcement learning to optimize charging efficiency. This model interacts with the battery environment, allowing the trained agent to autonomously determine the optimal charging profile, thus maximizing battery lifetime. The results show that this approach allows charging batteries in as little as 6–14 minutes, obtaining charging times up to four times shorter than traditional methods. In addition, the agent demonstrates the ability to adapt to variations in parameters such as electrode thickness, optimizing charging autonomously in different conditions.

Study [76] emphasizes how advanced battery and BMS technologies, enriched with ML, have improved safety and efficiency in EVs. Intelligent BMSs, which use ML models, are critical for vital functions such as SOC and cell balancing, thus improving the actual autonomy and safety of EVs. State-of-health (SOH) management of LIBs is another area where ML has had a significant impact. According to [77], ANNs have been successfully applied to predict and monitor SOH, a crucial factor for the safe and efficient operation of energy storage systems. These models can capture complex nonlinear relationships between multiple factors, such as voltage, current, and temperature, and the battery health state. Furthermore, [78] introduces a hybrid ML model for thermal modeling and battery diagnostics. This approach combines mechanistic models with data-driven tradeoffs, providing a powerful tool to prevent overheating and ensure safety during battery operation. Deep learning has proven to be a powerful tool for health status estimation thanks to its ability to learn complex relationships between input data and health indicators. Architectures such as feedforward, convolutional, recurrent neural networks (LSTMs and GRUs), and Transformers have been applied with promising results on data-driven models [80–82]. The authors of [79] demonstrate how deep learning is used to accurately estimate the SOC, SOH, and remaining useful life (RUL) of batteries. This approach enables more accurate and effective battery management, which is crucial for the safe and efficient operation of EVs [76,82].

Deep learning (DL) allows these states to be estimated from large sets of historical battery operation data, without the need for complex electrochemical models. Different architectures such as DNNs, recurrent networks (RNNs), LSTMs, and convolutional networks (CNNs) have been successfully applied [78,79]. Other works have applied LSTM networks, GRUs, and autoencoders to estimate the SOH and predict the RUL. For example, the model proposed by [83] based on an autoencoder with a particle filter achieved a mean square error of 12.1457 for the CALCE database, better than the particle filter and Kalman models. Finally, [84] analyzes different AI strategies, including SOH and SOC estimation. These strategies highlight the versatility and effectiveness of ML in various applications within BMSs, thus improving the performance and safety of EVs. Six ML algorithms are analyzed in this study: linear regression, random forest, gradient boosting, light gradient boosting machine, extreme gradient boosting, and support vector machines. The input data include current, temperature, and SOC, while voltage is used as the output [83,85]. The results show that the random forest provides superior performance with an R2 of 0.999 and minimal errors. This shows that ML can accurately estimate the state of lithium-ion batteries.

Therefore, the adoption of ML models in BMSs has opened a path towards more advanced and sustainable energy storage and EV systems. These advances are critical to improving the efficiency, safety, and lifespan of LIBs, marking a milestone in the transition to more efficient and environmentally friendly mobility. Studies [86,87] highlight the importance of these technologies in the future of battery management and electric mobility. Moreover, the integration of AI in LIB management is a growing area of research, with significant applications in EV and energy storage systems. Lithium-ion battery health management, especially in energy storage systems, has gained importance due to the need to manage SOH, SOC, and RUL accurately. ANN models are emerging as effective tools to address these challenges, leveraging their ability to decipher complex and nonlinear relationships between input data and battery health indicators [76,88,89]. On the other hand, accurate monitoring of the internal temperature distribution is crucial for the safety of LIBs. A novel approach to this is a hybrid thermal-neural network (LTNN) model that combines a mechanism-based distributed thermal model with machine learning-based axial thermal gradient compensation. This hybrid LTNN model has been shown to be highly compatible with common state observation methods, providing accurate and spatially resolved internal thermal monitoring and diagnostics for LIBs [78].

In the context of battery management systems (BMSs) in EVs, DL has emerged as a key technique to address battery-related algorithms and operational issues. The use of DL in BMS enables accurate estimation of SOC, SOH, and RUL, which is critical for EV reliability, safety, and performance [82,90]. The role of AI in solving battery management problems also extends to estimating the state of Li-ion batteries. Methods such as random forests, support vector machines (SVMs), and gradient momentum algorithms have demonstrated superior performance in discharge prediction, suggesting that integrating these methods with BMS can significantly improve the performance of EVs [84,91]. In addition, battery safety is a critical issue, especially in EVs and grid-scale storage. Fire incidents have highlighted the importance of battery safety, particularly regarding unpredictable thermal runaway. Machine learning approaches offer new opportunities to predict and prevent battery failures in practical applications, addressing multi-sector and multi-scale challenges [84,90]. AI and ML are playing a crucial role in improving the health and safety management of Li-ion batteries. These technologies offer promising solutions for accurate SOH, SOC, and RUL estimation, advanced thermal management, and failure and safety risk prevention in a variety of applications, including EVs and energy storage systems.

5. Challenges and Solutions in Extreme Conditions

Lithium-ion batteries, crucial in the era of electric mobility, face notable challenges in extreme temperature conditions. These conditions, defined outside the optimal operating range (298.15 K to 323.15 K), significantly impact battery efficiency and safety. At elevated temperatures, the acceleration of electrochemical degradation and the risk of thermal decomposition are primary concerns, while temperatures below the optimal range compromise battery capacity and power [92,93]. The challenge is intensified when considering that heat flow directly affects ionic and electronic conductivity, altering the redox processes at the electrodes and shortening the battery lifetime [94]. To address these difficulties, hybrid thermal management systems have been developed, combining liquid cooling with PCMs. These systems act as thermal buffers, passively absorbing and releasing heat during exothermic and endothermic reactions, thus keeping the temperature within a safe range and extending the battery lifetime [95]. Regulations such as ISO 12405-4 [96] and UN38.3 [97] play a crucial role, establishing maximum temperature limits of 55 °C and 60 °C. In addition, temperatures below 0 °C are considered extreme, although manufacturers often specify stricter ranges to optimize performance and durability. The importance of effective thermal management cannot be underestimated, especially when considering the wide variety of applications for these batteries, from EVs to energy storage in harsh environments [98,99].

In the future, thermal management systems will need to balance high capacity and fast charging with thermal efficiency, especially challenging over a wide temperature range. In addition, fast charging presents additional challenges, where optimization is key to controlling heat and temperature gradients while maintaining safety and performance [100,101]. Energy storage systems in harsh environments require advanced thermal management approaches, such as phase change cooling, to maintain stable performance under extreme conditions [102]. In addition, AI-based controllers, such as ANNs and fuzzy logic, are emerging as solutions to optimize battery safety and lifetime in EVs by dynamically adapting to temperature variations [103]. In conclusion, the effectiveness of thermal management in LIB is vital to overcome the challenges posed by extreme conditions. Continued development of advanced materials, techniques, and regulations is critical to ensure the performance, safety, and long-term viability of these essential technologies [94,98]. Table 3 provides a comprehensive examination of various thermal management technologies employed in BTMSs. The detailed analysis encompasses the technology's description, its relation to thermal leakage, specific benefits, and associated limitations and challenges. The technologies covered include hybrid systems, liquid cooling, PCM active heating systems, phase shift cooling, thermal management with AI, and thermotolerant separators. Each entry sheds light on the unique features, advantages, and considerations of the respective thermal management technology within the realm of BTMSs.

Table 3. Challenges and solutions in BTMSs.

Thermal Management Technology	Detailed Description	Relation to Thermal Leakage	Specific Benefits	Limitations and Challenges
Hybrid Systems Refs. [95,99]	The authors combine the efficiency of liquid cooling with the heat storage capacity of PCMs. They offer a dynamic and adaptive response to temperature variations.	They provide balanced thermal management, absorbing excess heat and releasing it when needed, which is crucial in fast-load or high-demand situations.	They significantly improve battery life and safety by adapting to different operating conditions.	They require a complex design and may have a higher cost.
Liquid Cooling Refs. [94,98,100,101]	It uses a fluid, usually water or a mixture of water and glycol, to efficiently transfer heat from the batteries to a heat exchanger. This technique is especially effective in fast charging or high-power density situations.	Essential to prevent overheating at high temperatures and maintain a stable thermal environment, reducing the risk of TR and battery degradation.	It provides fast and uniform heat dissipation, is scalable, and can be adjusted to different battery sizes and designs.	It can be susceptible to leaks and requires regular maintenance, in addition to an efficient pumping system.

Table 3. *Cont.*

Thermal Management Technology	Detailed Description	Relation to Thermal Leakage	Specific Benefits	Limitations and Challenges
PCM Refs. [49,102–104]	PCMs absorb and release heat during their phase transitions (solid to liquid and vice versa), allowing them to maintain a constant temperature in the battery. They are particularly useful in variable charge and discharge conditions.	They offer passive thermal response, stabilizing the internal temperature of the battery and reducing TR in extreme climates.	They provide high thermal storage capacity with minimal change in temperature, which is ideal for space-constrained applications.	They may have limitations in thermal conductivity and cycle life, as well as challenges in integration with other battery components.
Active Heating Systems Refs. [1,98,105]	These systems use heating elements or strategies such as battery preheating to maintain the optimum temperature in cold environments, thus improving battery response and efficiency.	They are essential to mitigate TR at low temperatures, ensuring that the battery operates efficiently and avoiding problems such as electrolyte crystallization.	Improve performance and safety in cold climates, extending battery life and preventing damage to internal components.	They increase energy consumption and may require additional time before use to reach optimum temperature.
Phase Shift Cooling Ref. [106]	It uses the evaporation and condensation of a refrigerant fluid to effectively absorb and dissipate heat. This method is based on the latent heat of phase change of the refrigerant, offering high heat dissipation capacity.	Efficiently controls temperature under peak load and unload, preventing overheating and excessive thermal runaway.	It offers precise thermal control and is capable of handling high thermal loads, making it suitable for energy-intensive applications.	It requires careful design to ensure the efficiency of the phase change system and can present challenges in refrigerant replenishment.
Thermal Management with AI Refs. [95,105]	It implements AI algorithms to monitor and adjust thermal management in real time, based on usage patterns and environmental conditions.	It enables fast and accurate response to temperature variations, optimizing thermal management to reduce TR and improve efficiency.	Maximizes battery life and performance by continuously adapting to changing conditions, improving safety and efficiency.	It depends on the accuracy of algorithms and data collection and may require constant updates and maintenance.
Thermotolerant Separators Ref. [107]	Advanced separators designed to withstand high temperatures without losing functionality, improving battery stability and safety in extreme heat conditions.	They prevent overheating and reduce TR by maintaining structural and functional integrity at high temperatures, avoiding internal short circuits.	They significantly increase safety in extreme conditions, resisting high temperatures without degrading.	They can increase the cost of battery manufacturing and present challenges in integration with other components.

6. Conclusions

This study on the thermal management of LIBs focuses on fundamental aspects of their sustainable and safe development, particularly in critical applications such as EVs and energy storage systems. This work highlights the cruciality of BTMSs in keeping LIBs within an optimal temperature range, optimizing their performance, and prolonging their lifetime. Current challenges include overheating and temperature variations, which can compromise the safety and performance of batteries, accelerating their aging and reducing their energy storage capacity. Significant innovations in materials and structures have been made that are revolutionizing thermal efficiency in LIBs. The use of PCMs is one such innovation, which helps to maintain battery temperature within a safe and constant range. However, these materials present the challenge of low thermal conductivity, which is being addressed by incorporating high-conductivity metal matrices and the addition of metal nanoparticles or porous materials.

The Integration of smart technologies and ML into battery and power distribution systems has emerged as a critical field. Models such as MSCC-DRL, which uses deep reinforcement learning, are making progress in optimizing charging efficiency and estimating the state of charge, health, and remaining life of batteries, indicating significant progress in intelligent battery management. Looking ahead, thermal management systems will need to balance high capacity and fast charging with thermal efficiency over a wide temperature range. Energy storage systems in harsh environments will require advanced thermal management approaches, and AI-based controllers are emerging as key solutions to optimize

EV battery safety and lifetime by dynamically adapting to temperature variations. Despite significant advances, challenges remain, including cost optimization, simplification of manufacturing processes, and effective integration of these solutions into large-scale battery systems. Continued research and development are critical to address these challenges and maximize the benefits of these advanced technologies.

The significant contribution of this research lies in its innovative approach to the thermal management of LIBs, especially highlighting the adoption of ML models in BMSs. This has paved the way towards more advanced and sustainable energy storage and EV systems, marking a milestone in the transition towards more efficient and environmentally friendly mobility. In summary, this study represents a crucial breakthrough in improving the efficiency, safety, and longevity of lithium-ion batteries, contributing significantly to the future of battery management and electric mobility.

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