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Review

A Compact Overview on Li-Ion Batteries Characteristics and Battery Management Systems Integration for Automotive Applications

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Abstract: The transition to sustainable mobility is progressing rapidly, with electric vehicles (EVs) playing a pivotal role in lowering greenhouse gas emissions and reducing the reliance on fossil fuels. At the core of this transformation are lithium-ion batteries (Li-ion), valued for their high energy density and long cycle life. However, the increasing demand for EVs necessitates continuous improvements in battery technology and the integration of advanced systems to ensure safe, efficient, and reliable performance. This review offers a clear and comprehensive summary of the latest innovations in Li-ion battery chemistry, battery pack design, and Battery Management System (BMS) functionalities. Unlike other reviews, this work emphasizes practical considerations, such as voltage, power, size, and weight for commercial vehicles. It also addresses integrated safety solutions, including disconnection systems and pre-charge circuits, which are vital for enhancing battery safety and lifespan. Additionally, it explores key BMS functions, like cell monitoring, balancing, and thermal management, all crucial for maximizing battery performance and ensuring safe operation. By consolidating current research and industry practices, this article provides essential information in a concise yet accessible format. It enables researchers to quickly gain a solid understanding of the field, distinguishing itself from reviews that focus on narrower aspects of battery technology. Its holistic approach delivers valuable insights for improving EV charging systems' safety and performance, making it a highly useful resource for researchers and industry professionals alike.

Keywords: lithium-ion batteries; battery management systems; state-of-charge estimation; electrochemical impedance spectroscopy; automotive; electric and hybrid vehicles

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1. Introduction

1.1. Motivations

The rapid transition towards sustainable mobility has placed electric vehicles (EVs) at the forefront of reducing greenhouse gas emissions and dependence on fossil fuels [1]. At the core of this revolution lie lithium-ion (Li-ion) batteries, renowned for their high energy density, scalability, and long cycle life, making them the preferred energy storage solution for automotive applications [2]. Despite their advantages, Li-ion batteries face several operational challenges that require advanced technological interventions to ensure safety, efficiency, and reliability. Among these challenges, thermal management stands out as critical, given the potential risks of overheating during rapid charging and discharging. Effective cooling mechanisms, such as liquid cooling systems or phase-change materials, are essential to maintain safe operating temperatures, though they often increase system complexity and costs. Similarly, safety concerns arise from the susceptibility of Li-ion batteries to overcharging, deep discharging, and short-circuits, all of which can lead to thermal runaway events. These risks necessitate sophisticated Battery Management Systems (BMSs) capable of real-time monitoring and controlling of battery parameters to enhance both performance and lifespan [3]. The BMS serves as a pivotal component in modern EVs, embedding advanced functionalities such as fault detection, state-of-charge (SOC) and state-of-health (SOH) estimation, and thermal management. These systems play a vital role in optimizing battery operation while addressing issues of capacity degradation over time, which is influenced by factors like operational temperature, depth of discharge, and charge/discharge cycles. Beyond operational challenges, the high production costs of Li-ion batteries, driven by the use of critical materials like cobalt and lithium, limit their widespread adoption. Efforts are underway to explore alternative materials and improve manufacturing processes to reduce costs while maintaining performance. Furthermore, recycling and disposal remain pressing concerns, as Li-ion batteries contain hazardous materials that necessitate specialized recycling infrastructure. This issue underscores the importance of developing efficient recycling technologies and implementing sustainable policies to mitigate environmental impact. Additionally, EV adoption is constrained by limitations in energy density and weight, which affect vehicle efficiency and performance, as well as by the scarcity and inefficiency of charging infrastructure in many regions. Investments in faster and more accessible charging technologies are essential to overcome these barriers and accelerate the EV transition. As advancements in battery chemistry and BMS algorithms continue to evolve rapidly, the need for a comprehensive understanding of these interconnected systems becomes increasingly critical [4]. This integrative approach not only addresses the current challenges but also lays the groundwork for enhancing the safety, performance, and sustainability of EV systems.

1.2. Literature Comparison and Authors' Contribution

The review stands out for its comprehensive coverage of lithium-ion battery chemistry, battery pack design, and BMS functionalities. This work provides a detailed examination of practical aspects such as voltage, power, size, and weight, along with the integration of safety methods, offering valuable insights for researchers and engineers. This holistic approach makes the work a significant contribution to the field of battery management for automotive applications. Compared to the article [5] on the integration of renewable energy sources into the power grid, which discusses the challenges and solutions for efficient energy management, this review offers a more detailed examination of BMS integration with lithium-ion batteries specifically for automotive applications. The attention to practical aspects of battery pack design and safety methods provides practical insights for engineers. While the paper [6] on advancements in battery management systems for electric vehicles emphasizes the need for improved safety and efficiency, this review provides a broader examination that includes battery chemistry, pack design, and BMS functionalities, making it applicable to a wider range of automotive applications. The study [7] on optimizing the thermal management of lithium-ion batteries introduces innovative cooling techniques and evaluates their effectiveness in maintaining battery performance and longevity. In contrast, this review offers a holistic view of BMS integration, covering not only thermal management but also cell monitoring, balancing, and safety methods. The research paper [8] on the development of smart grid technologies examines the potential benefits and challenges of implementing smart grids, including the impact on energy efficiency and reliability. This review integrates these smart grid strategies within the broader context of BMS and battery pack design. Compared to Das's article [9], which provides a general overview of battery management systems and future trends, this review offers a more detailed examination of BMS integration with lithium-ion batteries specifically for automotive applications. The attention to practical aspects of battery pack design and safety methods provides practical insights for engineers. While Velev et al. [10] focus on comparing different types of lithium-ion batteries for urban electric vehicles, this review provides a broader examination that includes battery chemistry, pack design, and BMS functionalities, making it applicable to a wider range of automotive applications. Le Duc Tai et al. [11] focus on thermal management systems for fast charging, a specific aspect of battery management. In contrast, this review offers a holistic view of BMS integration, covering not only thermal management but also cell monitoring, balancing, and safety methods. Rahmani et al. [12]

offer a detailed review of thermal management systems, similar to Le Duc Tai et al., yet this review integrates these thermal management strategies within the broader context of BMS and battery pack design. Polat et al. [13] focus on integrating battery energy storage systems (BESS) with DC fast chargers, a niche area, whereas this review's broader approach to BMS and battery pack design makes it more versatile and applicable to various aspects of EV technology. Mathew et al. [14] concentrate on battery resistance estimation techniques, a specific technical aspect of BMS. This review covers a wider range of topics, including battery chemistry, pack design, and multiple BMS functionalities. Collin et al. [15] review fast-charging technologies, focusing on the impact on battery systems. This review provides a broader examination that includes not only charging but also battery chemistry, pack design, and BMS functionalities. Dar et al. [16] concentrate on onboard chargers, a specific component of EV technology, while this review's broader approach to BMS and battery pack design offers a more comprehensive understanding of the entire battery management ecosystem. Tawonezvi et al. [17] focus on lithium-ion battery recycling, an important aspect of battery lifecycle management. However, this review provides a broader examination that includes battery chemistry, pack design, and BMS functionalities. The article by Moulik and Söffker [18] centers on future advancements in BMS technology. In contrast, this review provides a more detailed examination of current BMS functionalities and practical design considerations. Zentani et al. [19] concentrate on various fast-charging techniques and infrastructure, whereas this review provides a broader examination that includes battery chemistry, pack design, and BMS functionalities. This versatility makes it applicable to a wider range of automotive applications. The World Electric Vehicle Journal article [20] focuses on a specific battery pack simulation, whereas this review provides a comprehensive overview of BMS integration, covering various aspects of battery management and safety. Yao et al. [21] focus on State-of-Health (SoH) estimation methods, while this review covers a broader range of topics, including battery chemistry, pack design, and BMS functionalities. Garud et al. [22] concentrate on cooling strategies for battery thermal management, while this review provides a broader examination that includes multiple aspects of BMS and battery pack design. Makeen et al. [23] focus on fast-charging protocols, while this review provides a broader examination that includes battery chemistry, pack design, and BMS functionalities. Xu et al. [24] center on recycling and regenerating materials from spent lithium-ion batteries, while this review provides a broader examination that includes battery chemistry, pack design, and BMS functionalities. He et al. [25] focus on recycling technologies and market trends, while this review provides a broader examination that includes battery chemistry, pack design, and BMS functionalities. Sanguesa et al. [26] provide a broad review of EV technologies and challenges, while this review focuses specifically on lithium-ion batteries and BMS integration. Suanpang and Jamjuntr [27] focus on using Q-learning for battery management, while this review provides a broader examination that includes various aspects of BMS and battery pack design. The review on modeling and SOC/SOH estimation of batteries for automotive applications presented in [28] provides an in-depth analysis of state-of-the-art SOC and SOH estimation algorithms for lithium-ion batteries. Compared to this focused review, the broader scope of battery chemistry, pack design, and BMS functionalities offers a more comprehensive understanding of battery management for automotive applications. The overview on battery charging systems for electric vehicles presented in [29] explores the significance and challenges of bi-directional electric vehicles, focusing on various circuit architectures of on-board chargers (OBCs). This review provides a detailed examination of OBCs; the broader examination of BMS integration, including safety methods and practical design considerations, offers a more holistic view of battery management systems. In conclusion, the review stands out for its comprehensive coverage of lithium-ion battery chemistry, battery pack design, and BMS functionalities. The detailed examination of practical aspects, such as voltage, power, size, and weight considerations, along with the integration of safety methods, provides valuable insights for researchers and engineers.

This holistic approach makes it a significant contribution to the field of battery management for automotive applications.

2. Methodology

This review aims to provide a comprehensive and structured analysis of advancements in Li-ion battery technology and BMS integration for automotive applications. To ensure credibility and clarity, a systematic approach was adopted for selecting and analyzing the literature.

2.1. Literature Selection Process

The literature was sourced from established academic databases, including Scopus, Web of Science, and IEEE Xplore, using specific keywords tailored to the topic. The following keyword combinations were employed:

- Li-ion batteries AND BMS integration
- Lithium-ion batteries AND automotive applications
- Battery Management Systems AND thermal management
- State-of-Charge estimation AND electric vehicles.

The search also included variants focusing on emerging topics, such as Li-ion batteries AND aerospace applications and cross-industry BMS.

2.2. Inclusion and Exclusion Criteria

To refine the results, the following inclusion and exclusion criteria were applied:

- Inclusion Criteria:
  - Peer-reviewed journal articles (preferred) and conference proceedings.
  - Studies published between 2018 and 2024, ensuring coverage of the most recent advancements.
  - Articles from well-established editorial: IEEE, Elsevier, IET, Wiley, MDPI.
  - Articles addressing automotive applications, Li-ion battery chemicals, or specific BMS functionalities.
  - Foundational studies offering key insights into battery technology and management systems.
- Exclusion Criteria:
  - Non-peer-reviewed sources, such as blogs and editorials.
  - Articles focusing exclusively on unrelated battery chemicals (e.g., lead-acid or nickel-metal hydride).
  - Studies with limited technical detail or not directly related to automotive applications.

2.3. Review Scope and Timeline

The review encompasses a wide temporal range, emphasizing recent publications to capture state-of-the-art advancements. Foundational studies from earlier periods were selectively included to provide essential context, especially regarding Li-ion battery materials, pack design, and BMS algorithms. The literature review process involved multiple stages:

1. Preliminary Screening: Titles and abstracts were initially reviewed to assess relevance to the topic.
2. Detailed Analysis: Full-text articles were examined to identify technical contributions, methodologies, and findings relevant to Li-ion batteries and BMS.
3. Synthesis and Categorization: Findings were categorized into themes such as battery chemistry, BMS functionalities (e.g., thermal management, SoC estimation), safety mechanisms, and cross-industry applications.

2.4. Contributions from the Reviewed Literature

The review consolidates advancements from diverse domains:

- Battery Chemistry: Evaluating materials such as NMC, NCA, and $LiFePO_4$ for automotive applications.
- BMS Algorithms: Analyzing SoC estimation methods, including Coulomb Counting, Kalman Filtering, and AI-based models.
- Safety Mechanisms: Discussing innovative thermal management systems, pre-charge circuits, and disconnection switches.
- Cross-Industry Potential: Exploring the adaptability of Li-ion batteries and BMS for aerospace and satellite technologies.

2.5. Limitations of the Review

- The reliance on keyword searches may inadvertently exclude some relevant studies due to variations in terminology.
- The review focuses on articles written in English, potentially overlooking contributions in other languages.
- Some industry-specific advancements may not be included due to the proprietary nature of certain technologies.

3. Li-Ion Battery Cells Characteristics

3.1. Chemical Materials for Lithium-Ion Batteries

Lithium-ion batteries (LIBs) rely on a combination of carefully chosen materials to achieve optimal performance, safety, and longevity. The primary components—anode, cathode, electrolyte, and separator—significantly influence the overall capabilities and limitations of the batteries. This section highlights key advances in material science, discusses trade-offs, and identifies areas requiring further innovation.

- Anode Materials: Graphite remains the dominant anode material due to its balance of cost, electrical conductivity, and structural stability. However, its limited capacity constrains the energy density of LIBs. Lithium titanate ($Li_4Ti_5O_{12}$), though safer and with a longer cycle life, suffers from lower energy density, limiting its use to applications prioritizing safety, such as stationary energy storage and public transportation. Future developments could explore silicon-based anodes, which promise significantly higher capacities but face challenges related to volumetric expansion and structural degradation during cycling.
- Cathode Materials: Cathode materials define the energy density, voltage, and cost of LIBs, with notable advances and persistent trade-offs:
  - Lithium Cobalt Oxide ($LiCoO_2$) offers high energy density but has limitations in thermal stability and cost, making it more suited for portable electronics than EVs.
  - Lithium Iron Phosphate ($LiFePO_4$) emphasizes thermal stability and cycle life at the expense of energy density, making it ideal for applications prioritizing safety over performance.
  - Nickel Manganese Cobalt (NMC) cathodes balance energy density, cost, and safety, but their performance depends on nickel content, with higher nickel ratios offering greater energy density but introducing thermal instability.
  - Nickel Cobalt Aluminum (NCA) provides some of the highest energy densities available but poses challenges in thermal management, requiring sophisticated cooling and BMS solutions for use in high-performance EVs.

  Future research should focus on reducing reliance on cobalt and increasing nickel content while addressing safety and sustainability concerns.
- Electrolyte Materials: Current LIB electrolytes, such as lithium hexafluorophosphate ($LiPF_6$) dissolved in organic carbonates, provide high ionic conductivity but are prone to decomposition at high temperatures, posing safety risks. Advances in solid

electrolytes or non-flammable liquid formulations could mitigate these risks and support next-generation battery chemicals.

- Separator Materials: Polyethylene (PE) and polypropylene (PP) separators remain standard due to their mechanical strength and chemical stability. However, high temperatures can cause shrinkage, leading to potential short-circuits. Coated or ceramic separators offer improved thermal resistance and are an area of ongoing development.

Table 1 resumes the main chemical materials used for lithium-ion batteries and Table 2 shows chemicals for EVs batteries.

Table 1. Comparison of chemical materials for lithium-ion batteries.

Component	Material	Advantages	Disadvantages	Applications
Anode	Graphite	High conductivity, stable structure	Lower capacity compared to alternatives	Consumer electronics, EVs
Anode	$Li_4Ti_5O_{12}$	High safety, long cycle life	Lower energy density	High-safety applications
Cathode	$LiCoO_2$	High energy density, stable performance	Expensive, thermal instability	Consumer electronics
Cathode	$LiFePO_4$	Excellent thermal stability, long cycle life	Lower energy density	Power tools, EVs
Cathode	NMC	Balanced performance, cost-effective	Moderate thermal stability	EVs, grid storage
Cathode	NCA	High energy density, good lifespan	Expensive, moderate safety	High-performance EVs
Electrolyte	$LiPF_6$ in EC/DMC	High ionic conductivity, stability	Sensitive to moisture, can decompose at high temperatures	All LIBs
Separator	PE/PP	Good mechanical strength, chemical stability	Can shrink at high temperatures	All LIBs

Table 2. Comparison of lithium-ion battery chemicals for electric vehicles.

Chemical	Energy Density (Wh/kg)	Pros	Cons	Applications
Lithium Cobalt Oxide ($LiCoO_2$)	150–200	High energy density, fast charging	Low thermal stability, safety concerns	Portable electronics
Lithium Iron Phosphate ($LiFePO_4$)	100–170	High thermal stability, long cycle life	Lower energy density	EVs, energy storage systems
Nickel Manganese Cobalt (NMC)	Up to 200	Balanced performance, customizable properties	Higher cost compared to LFP	EVs, industrial storage

Table 2. *Cont.*

Chemical	Energy Density (Wh/kg)	Pros	Cons	Applications
Nickel Cobalt Aluminum (NCA)	250–300	Very high energy density	Thermal management challenges	High-performance EVs (e.g., Tesla)
Lithium Titanate (LTO)	<100	Long life, excellent thermal stability	Low energy density	High-power EVs, buses
Lithium Sulfur (Li_2S)	Up to 2700 (theoretical)	Lightweight, low environmental impact	Low stability, limited cycle life	Future high-energy applications

3.2. Li-Ion Cells Features

Li-ion battery life is commonly expressed in charge cycles, which indicate the number of times a battery can be charged and discharged before losing significant capacity. High-quality batteries can achieve between 2000 and 3000 cycles, while lower-quality batteries are limited to 300–500 cycles. Cycle life is heavily influenced by factors such as the operating temperature, depth of discharge, and charge/discharge rates, underscoring the need for effective thermal management and precise BMS algorithms.

It is important to note that a full cycle only occurs when the battery is completely discharged and then recharged to 100%. Partial charges, however, can extend the useful life of the battery. This highlights the importance of adaptive charging protocols and SoC estimation algorithms to prevent overcharging or deep discharging, which can accelerate capacity fade. Battery safety is strongly influenced by the battery's chemistry. For example, $LiCoO_2$ batteries present risks of overheating and potential explosion if damaged, while $LiFePO_4$ batteries offer greater thermal stability and safety. Thermal runaway remains a critical challenge, particularly for high-energy-density materials like NCA and NMC, necessitating advancements in thermal management systems (TMS).

Li-ion battery form factors directly influence fit, manufacturing efficiency, and electrical behavior. In Figure 1, some available battery shapes are illustrated. Cylindrical cells, commonly used in electric vehicles, offer high energy density and good heat dissipation, but their rigid shape can limit the flexibility of battery pack design. Prismatic cells, on the other hand, due to their rectangular shape, can be stacked densely and offer better heat management, but have higher manufacturing costs and potential safety issues. Pouch cells, flexible and lightweight, fit into tight spaces and offer good energy density, but are more susceptible to mechanical damage and have less efficient heat dissipation. Table 3 shows the main aspects of each possible form factor for lithium-ion batteries.

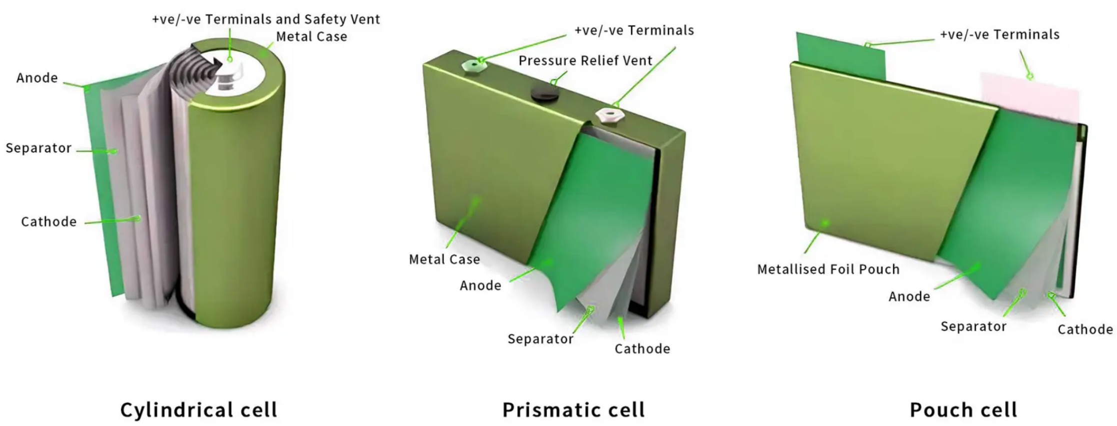

Figure 1. Example of available battery shapes.

Table 3. Comparison of lithium-ion battery form factors.

Form Factor	Typical Chemicals Used	Thermal Management	Mechanical Stress	Deforming During Use	Space Utilization	Energy Density	Cost (per kWh)	Cycle Life	EV Compatibility
Cylindrical	$LiCoO_2$, NMC, $LiFePO_4$	Good heat dissipation	High resistance	Low	Moderate	High (150–200 Wh/kg)	Low-Moderate	1000–1500 cycles	Common in Tesla EVs
Prismatic	NMC, $LiFePO_4$	Better contact surface	Moderate	Moderate	High	Moderate (100–200 Wh/kg)	Moderate	1500–2000 cycles	High for compact EVs
Pouch	$LiCoO_2$, NCA, $LiFePO_4$	Inferior to others	Low resistance	High	High	High (100–250 Wh/kg)	High	1000–2000 cycles	High for flexible designs

Emerging trends, such as solid-state batteries, aim to combine the benefits of existing form factors while addressing their limitations, including mechanical stress and thermal stability. These innovations could further enhance the compatibility of Li-ion batteries with compact and high-performance EV designs. The choice of form factor also affects the overall design of the battery pack, requiring attention to safety and thermal management requirements. BMS systems are pivotal in optimizing form factor-specific performance by balancing cells and managing heat dissipation effectively. Advances in integrated cooling methods, such as liquid cooling for cylindrical cells and phase-change materials for pouch cells, are key areas for innovation. Continued innovation in materials and form factors, such as solid-state cells, promises to optimize battery performance, making this topic increasingly relevant in the field of sustainable energy [30].

4. Practical Aspects in Battery Pack Design

Designing battery packs for commercial vehicles requires a compromise among several technical factors, which vary depending on the intended use. In long-haul trucks, energy capacity is essential to ensure range, with battery packs of 300 kWh or more. In contrast, for urban vehicles, such as delivery vans, a 50 kWh pack is sufficient, prioritizing weight and size over capacity. Voltage plays a key role: 800 V systems are necessary in high-performance vehicles to improve efficiency and reduce charging times, while in light vehicles, 400 V may suffice, focusing more on battery pack integration. Power is also crucial in heavy-duty vehicles, where high output is needed to support demanding loads or difficult terrain, while in light vehicles the power requirement is more modest. Size is critical in urban contexts where cargo space is limited, but less critical for heavy-duty trucks, where energy capacity is the priority. Finally, weight is a key factor in light vehicles to improve efficiency and payload capacity, while in heavy vehicles it is less decisive, as they are designed to handle high loads [31]. Table 4 shows the typical technical parameters for battery pack design in commercial vehicles.

Designing battery modules and packs for commercial vehicles is a highly technical process that requires a meticulous combination of series and parallel cell connections to optimize the desired voltage, capacity and power characteristics. Cell connections are critical to achieving the required performance and can be accomplished in a variety of ways. Series connection of cells is a method used to increase the total voltage of the battery pack. In this configuration, the positive terminals of one cell are connected to the negative terminals of the next cell [32]. In Figure 2, some connection typologies are shown.

Table 4. Technical parameters for battery pack design in commercial vehicles.

Parameter	High-Demand Applications (e.g., Trucks)	Low-Demand Applications (e.g., Urban Vans)	Typical Values
Energy Capacity	Crucial for long range (300 kWh or more)	Lower demand (50 kWh is sufficient)	50–300 kWh
Voltage	800 V for efficiency and fast charging	400 V sufficient for lighter loads	400–800 V
Power Output	High power for heavy loads and tough terrain	Moderate power for city deliveries	50–200 kW
Dimensions	Less critical, more space available	Crucial to maximize cargo space	Varies by design
Weight	Less important, trucks handle heavier batteries	Critical for improving efficiency	Varies (lighter for vans)

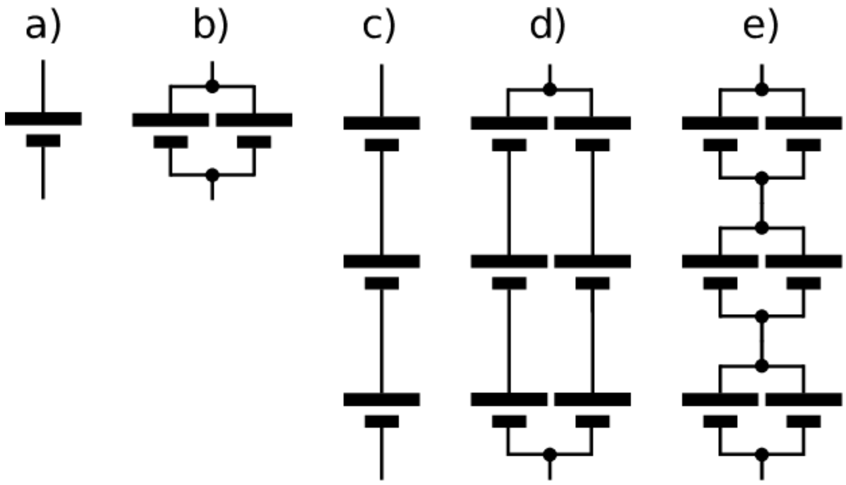

Figure 2. Schematic representations of different battery pack topologies: (**a**) single cell; (**b**) parallel connection of two cells; (**c**) series connection of three cells; (**d**) parallel connection of two strings of three serially connected cells; (**e**) series connection of three modules consisting of two cells connected in parallel.

The total voltage of the battery pack is then the sum of the individual voltages of all cells connected in series, while the capacity remains equivalent to that of a single cell. For example, using lithium-ion cells with a nominal voltage of 3.7 V and a capacity of 3 Ah, connecting 10 cells in series results in a battery pack with a total voltage of 37 V (3.7 V $\times$ 10) and a capacity of 3 Ah. This configuration is frequently used in light electric vehicles, such as electric bicycles, where a relatively high voltage is needed along with a moderate capacity. On the other hand, parallel connection of cells is used to increase the total capacity of the battery pack. In this configuration, all positive terminals are interconnected and all negative terminals are joined. As a result, the total voltage remains the same as for a single cell, while the total capacity is the sum of the capacities of the cells connected in parallel. For example, using the same 3.7 V and 3 Ah cells, connecting 10 cells in parallel results in a battery pack with a total voltage of 3.7 V and a capacity of 30 Ah (3 Ah $\times$ 10). This configuration is particularly useful in applications that require large capacity, such as home energy storage systems or commercial vehicles that need a long range. To simultaneously achieve both high voltage and substantial capacity, it is common to combine series and parallel connections. This strategy is prevalent in commercial vehicle battery packs, where balancing both characteristics is key. For example, to build a battery pack with a voltage of 37 V and a capacity of 30 Ah, you can connect 10 cells in series (to get 37 V) and then assemble 10 of these groups in parallel (to reach 30 Ah). In total, the battery pack will consist of 100 cells (10 in series $\times$ 10 in parallel). This configuration is typical for commercial vehicles such as electric vans, which need a combination of high voltage and large capacity to ensure adequate performance and sufficient autonomy [33]. In terms of electrical connections, the interconnections between the cells that build a module and among the modules of the same battery pack are made using solid conductors known as "busbars" [34]. These conductors must be designed to handle high currents and minimize energy losses, and are generally made of copper or aluminum for their high electrical conductivity. The design of busbars must consider various factors, including electrical resistance and heat dissipation, in order to ensure safe and efficient operation during prolonged operation. Another crucial aspect in the design of battery packs is thermal management. Modules can be equipped with active or passive cooling systems to keep cells within an optimal operating temperature range, as high temperatures can reduce cell life and compromise safety. For example, in heavy-duty commercial vehicles such as electric trucks, battery packs can be equipped with liquid cooling systems to dissipate heat generated during heavy use. These systems help prevent overheating and extend cell life, thereby improving operational safety [35]. Recently, innovative RFID-based sensored tags for environmental monitoring have been developed [36]. Effective thermal management is essential for maintaining the performance and safety of lithium-ion batteries in electric vehicles. Integrated cooling systems can be categorized into active and passive methods. Active cooling systems, such as liquid cooling and forced air cooling, provide efficient heat dissipation but require additional components and energy. Passive cooling systems, including phase change materials and heat sinks, rely on natural convection and conduction, offering simpler and more energy-efficient solutions. The choice of cooling system depends on the specific application and design constraints of the battery pack. Table 5 resumes the main aspects of cooling systems.

Table 5. Types and characteristics of integrated cooling systems in battery packs.

Cooling System	Description	Advantages	Examples
Liquid Cooling	Liquid coolant	High efficiency, high power	Tesla Model S, BMW i3
Forced Air Cooling	Fans, airflow	Low cost, simple	Nissan Leaf, Chevrolet Bolt
Phase-Change Materials (PCM)	Heat absorption, phase change	No moving parts, efficient	Prototypes, emerging tech
Heat Sinks	Metal fins	Passive, simple	Industrial use

Integrated cooling systems are crucial for preventing thermal runaway, extending battery life, and ensuring the overall safety and reliability of electric vehicles. The choice of cooling system must balance efficiency, cost, complexity, and the specific thermal management needs of the vehicle.

5. Integrated Safety Methods

5.1. Disconnection Systems

Disconnect switches are essential components in battery circuits for a variety of reasons, including safety, ease of maintenance and protection of system components. Their integration is crucial in high-use environments such as commercial and electric vehicles. Isolating the battery from the circuit is vital to prevent short-circuits, which can cause electrical fires. Disconnect switches provide a mechanism to quickly interrupt the flow of current in the event of a fault. They are designed to meet specific safety standards, such as UL (Underwriters Laboratories) and IEC (International Electrical Commission) regulations, which set minimum requirements for the design and construction of electrical components [37].

Integrating disconnect switches simplifies battery maintenance and replacement, allowing rapid interventions without the need to disconnect the entire system. This is particularly important in commercial applications, where downtime must be kept to a minimum. These switches can be designed to allow battery replacement without compromising the safety of the system, thus avoiding exposure to dangerous voltages. Disconnect switches play a crucial role in protecting sensitive electronics from over-voltages and over-currents. These events can occur in short-circuit or overload conditions, and switches can act as a safeguard, interrupting the flow of current before permanent damage occurs. Additionally, some models integrate additional protection circuitry, such as fuses and relays, for even greater safety [38]. Disconnect switches are also used to manage energy, disconnecting the battery when it is not in use. This helps prevent deep discharge, which can significantly reduce the life of the cells. Switches can be programmed to activate automatically when the system enters idle mode, helping to improve overall energy efficiency [39]. Table 6 provides a comparison among the different type of disconnecting systems.

Table 6. Comparison of electro-mechanical and solid-state switches.

Aspect	Electro-Mechanical Switches	Solid-State Switches
Operation Mechanism	Mechanical contacts, physical movement	Semiconductors, no moving parts
Interruption Speed	Slower, 10–100 ms	Fast, <10 μs
Reliability	Subject to wear and tear	High, no mechanical wear
Cost	Lower, economical	Higher, advanced technology
Electric Arc Generation	Prone to arcs, requires protection	Minimal risk, safer
Heat Dissipation	Low heat, minimal cooling	Higher heat, requires cooling
Installation Complexity	Simple, easy integration	Complex, needs specialized design
Advantages	• Durable and reliable • Lower cost • Easy installation	• Fast interruption • No moving parts • Safe, minimal arc risk
Disadvantages	• Slow interruption • Mechanical wear • Arc generation	• Higher cost • Heat dissipation • Complex integration
Preferred Applications	• Light commercial vehicles • Backup systems	• Heavy electric vehicles • Energy storage systems

5.2. Pre-Charge Circuit

The pre-charge circuit plays a pivotal role in the design of Li-ion battery systems, especially in high-power applications such as EVs and energy storage systems. It protects the battery and electronic components during the startup phase, preventing over-currents and short-circuits. In critical scenarios, the absence of a pre-charge circuit can lead to significant risks, such as system failure or reduced battery life.

- Safety: reduces the risk of short-circuits and fires by stabilizing current and voltage [40].
- Protection: prevents damage to control circuits and inverters, which can be sensitive to sudden current spikes [41].
- Efficiency: improves energy efficiency by minimizing energy losses during the activation phase [42].

Table 7 resumes the main working conditions of a Li-ion battery with and without the pre-charge circuit.

Table 7. Comparison of conditions with and without pre-charge circuit in Li-ion batteries.

Aspect	With Pre-Charge Circuit	Without Pre-Charge Circuit
Initial Voltage	Gradually stabilized, avoiding spikes	Voltage spikes that may damage the battery
Initial Current	Limited to safe values (e.g., 1A)	High initial current, possibly exceeding nominal values
Over-voltage	Controlled; protects electronic components	Possible overvoltage causing malfunctions or failures
Efficiency	Higher energy efficiency during activation	Lower efficiency due to energy losses
Battery Lifespan	Increased longevity due to reduced wear	Accelerated wear due to frequent over-currents
Maintenance Costs	Lower, thanks to component protection	Higher maintenance costs for repairs and replacements

6. Battery Management System (BMS) Functionalities

A BMS has the primary job of monitoring and balancing the cells within a battery pack. This system constantly monitors the voltage, current, and temperature of each cell to ensure they are operating within safe limits. Monitoring voltage is essential to prevent overcharging or deep discharging cells, while temperature control helps prevent overheating, which could lead to dangerous situations such as thermal runaway. Cell balancing, a critical function for battery pack efficiency and life, is achieved by equalizing the state of charge of individual cells. This process can be implemented through passive balancing, which discharges excess energy as heat, or active balancing, which transfers excess energy from one cell to another. Another key function of a BMS is estimating the SoC and other vital parameters for managing battery performance such as the temperature and eventual shape deformation. The SoC represents the amount of charge remaining, expressed as a percentage of the total battery capacity. Several methods are used to estimate the SoC, but they still face significant challenges, particularly in dynamic or extreme conditions. There are several methods to accurately estimate the SoC:

- Coulomb Counting (Ah counting) calculates the SoC by integrating the current over time, but can accumulate errors due to measurement drift, especially during long usage periods. This method requires frequent recalibration and is sensitive to low accuracy over time.
- The Open-Circuit Voltage (OCV) method, which estimates the SoC by measuring the battery's quiescent voltage, is accurate but requires the battery to be in a stable quiescent state (i.e., no load must be applied during such measurement). This requirement limits its practicality during continuous operation.
- More sophisticated methods, such as model-based estimation using Extended Kalman Filters, combine current, voltage, and temperature data with mathematical models of the battery's behavior for more accurate estimates, even under dynamic conditions. However, these models are often highly complex and require significant computational resources, which may not always be feasible for real-time applications.
- Another approach used, especially in research settings, is Electrochemical Impedance Spectroscopy (EIS), which provides high-precision estimates using impedance measurements. While precise, this method is slow and difficult to integrate into standard BMS systems for real-time use.

The BMS also takes care of battery pack protection and safety management. In the event of overvoltage, it disconnects the circuit to prevent overcharging, while protecting against deep discharge with under-voltage protection by disconnecting the load. There is also overcurrent protection to prevent the current from exceeding safe limits during the charging or discharging process. In addition, the BMS prevents overheating with thermal protections, and in the event of a short-circuit, it immediately cuts off the current flow to prevent damage or fire. Thermal management, in particular, remains a significant challenge, especially in high-power applications like electric vehicles, where the system must efficiently manage heat dissipation to prevent thermal runaway. Another key function of the BMS is controlling the charging and discharging of the battery pack. During the charging phase, the system manages the current and voltage to prevent the battery from being overcharged, a critical aspect in lithium-ion batteries. During the discharging phase, the BMS ensures that the current does not exceed safe limits, protecting the battery and the devices connected to it. Despite advancements, ensuring optimal charging and discharging rates under varying operational conditions remains an area where improvements are needed, particularly for fast-charging scenarios. To ensure that the battery operates within an optimal temperature range, especially in high-power applications, such as electric vehicles, the BMS also manages the cooling of the battery. This can be done through active cooling, using fans or liquid cooling systems, or through passive cooling, using heat sinks or natural cooling. Active cooling systems, though effective, add complexity and weight to the system, and passive cooling may not be sufficient for high-performance batteries, making this an ongoing area of research and development. In terms of communication and diagnostics, the BMS exchanges data with other systems and constantly monitors battery performance to detect abnormal conditions. Communication protocols such as CAN, SMBus, and I2C allow the BMS to communicate with vehicle control systems or external monitoring units. In addition, the system records data for predictive maintenance and troubleshooting by monitoring various parameters including voltage, current, and temperature. The integration of real-time diagnostics for predictive maintenance, while promising, faces challenges in terms of data accuracy and the need for advanced data processing algorithms to predict failures accurately. Another important feature of the BMS is the management of the pre-charge circuit, which limits the inrush currents during start-up, protecting the power electronics from current peaks. In addition, the system takes care of insulation management, ensuring electrical isolation between high-voltage and low-voltage components, thus preventing dangerous conditions. In complex energy systems, such as hybrid vehicles or renewable energy storage systems, the BMS optimizes energy distribution. It takes care of load management, prioritizing power distribution to critical subsystems, and can also manage energy recovery, for example, in electric vehicles, optimizing regenerative braking to extend the vehicle's range. However, optimizing energy distribution, especially in scenarios with varying loads and power demands, still presents challenges in terms of real-time decision-making and system coordination.

7. Algorithms for SOC Estimation Integrated in the BMS

7.1. Coulomb Counting

The Coulomb Counting method is one of the simplest and most straightforward techniques for estimating the state of charge (SoC) of lithium batteries. This method relies on integrating the current flowing into and out of the battery over time. The basic mathematical formulation is:

$$SoC(t) = SoC(t_0) + \frac{1}{C_{nom}} \int_{t_0}^{t} I_{batt}\, dt \tag{1}$$

In this equation, $SoC(t)$ represents the estimated state of charge at time t, while $SoC(t_0)$ is the initial state of charge at time t_0. The nominal capacity of the battery is denoted by C_{nom}, and I_{batt} is the battery current, which is positive during charging and negative during discharging. The integration is performed over time, from the initial time t_0 to the current time t. It results in a non-dimensional SoC variable. One of the main advantages of the Coulomb Counting method is its computational simplicity. Implementing this method is relatively straightforward, as it only requires measuring the current and time. Additionally, it is computationally efficient since integrating the current is a basic mathematical operation. This method provides a real-time estimate of the SoC, which is very useful for continuous battery monitoring. However, the method also has some significant drawbacks. One of the primary issues is the accumulation of errors. Measurement errors in the current can accumulate over time, leading to an inaccurate SoC estimate. Furthermore, the accuracy of the estimate heavily depends on the precise knowledge of the initial SoC [43]. If the initial SoC is not accurately known, the entire estimate can be erroneous. Another disadvantage is that the battery's capacity can vary with aging and operating conditions, affecting the method's accuracy. Finally, current sensors can introduce noise and disturbances, further degrading the accuracy of the estimate. Despite these drawbacks, the Coulomb Counting method is considered reliable for applications where absolute precision is not critical. Its simplicity makes it a popular choice, but it is important to take measures to mitigate accumulated errors and variations in battery capacity. To improve accuracy, Coulomb Counting can be combined with other methods, such as Kalman Filtering, which helps correct accumulated errors and provides a more accurate SoC estimate [44].

7.2. Open-Circuit Voltage

The Open-Circuit Voltage (OCV) method is a widely used technique for estimating the state of charge (SoC) of lithium-ion batteries. This method relies on the relationship between the battery's open-circuit voltage and its SoC. When the battery is at rest, meaning no current is flowing in or out, the voltage measured across its terminals is the open-circuit voltage. This voltage has a well-defined relationship with the SoC, which can be used for estimation purposes. The relationship between the OCV (expressed in volts) and SoC can be expressed as follows:

$$OCV = f(SoC) \tag{2}$$

where f is a function that describes the OCV as a function of the SoC. This function is typically determined empirically through extensive testing and modeling. Various models can be used to fit the OCV-SoC curve, including polynomial, exponential, and Gaussian models. For example, a polynomial model might look like:

$$OCV(SoC) = a_0 + a_1 \cdot SoC + a_2 \cdot SoC^2 + \ldots + a_n \cdot SoC^n \tag{3}$$

where $a_0, a_1, \ldots, a_n$ are the coefficients determined through curve fitting. One of the main advantages of the OCV method is its accuracy when the battery is at rest. Since the OCV is directly related to the SoC, this method can provide a precise estimate under stable conditions. Additionally, the OCV method does not suffer from cumulative errors like the Coulomb Counting method, as it relies on a direct measurement rather than integration over time [45]. However, the OCV method also has its drawbacks. One significant limitation is that it requires the battery to be at rest for an accurate measurement. This means that the battery must be disconnected from any load or charging source for a period, which can be impractical in many real-world applications. The resting period can vary depending on the battery chemistry and state, but it typically ranges from several minutes to several hours. Another challenge is the hysteresis effect, where the OCV for a given SoC can differ depending on whether the battery is being charged or discharged. This can introduce errors in the SoC estimation if not properly accounted for. From a computational perspective, the OCV method is relatively simple. Once the OCV-SoC relationship is established, estimating the SoC involves measuring the OCV and applying the pre-determined function. This makes the method computationally efficient, as it primarily involves a lookup or evaluation of a mathematical function. In practice, the OCV method is often used in combination with other methods to improve overall accuracy and reliability. For instance, it can be combined with Coulomb Counting to correct for cumulative errors during periods when the battery is at rest. Additionally, advanced techniques like Kalman Filtering can be used to fuse OCV measurements with other data to provide a more robust SoC estimate [46].

In summary, the OCV method is a valuable tool for SoC estimation due to its accuracy under stable conditions and computational simplicity. However, its reliance on resting periods and sensitivity to hysteresis effects must be carefully managed to ensure reliable performance in practical applications.

7.3. Model-Based Methods

Model-based methods are widely used for estimating the state of charge (SoC) of lithium-ion batteries due to their ability to accurately represent the dynamic behavior of the battery. These methods rely on mathematical models that describe the internal processes and characteristics of the battery. One of the most common approaches is the use of Equivalent Circuit Models (ECMs), which represent the battery using electrical components such as resistors, capacitors, and voltage sources [47]. The simplest form of an ECM is the RC (resistor-capacitor) model, which can be expressed as:

$$V_{batt} = OCV - I_{batt} \cdot R_0 - V_{RC} \tag{4}$$

where V_{batt} is the terminal voltage of the battery, OCV is the open-circuit voltage, I_{batt} is the battery current, R_0 is the internal resistance, and V_{RC} is the voltage across the RC network. The voltage V_{RC} can be described by the differential equation:

$$\frac{dV_{RC}}{dt} = \frac{I_{batt}}{C_1} - \frac{V_{RC}}{R_1 \cdot C_1} \tag{5}$$

where R_1 and C_1 are the resistance and capacitance of the RC network, respectively. Another advanced model is the Single-Particle Model (SPM), which simplifies the battery to a single spherical particle representing the active material [48]. The SPM can be described by the following equations:

$$\frac{\partial c_s}{\partial t} = \frac{D_s}{r^2} \frac{\partial}{\partial r}\left(r^2 \frac{\partial c_s}{\partial r}\right) \tag{6}$$

$$I_{batt} = -nFA_s D_s \left.\frac{\partial c_s}{\partial r}\right|_{r=R_s} \tag{7}$$

where c_s is the concentration of lithium ions in the solid phase, D_s is the diffusion coefficient, r is the radial coordinate, n is the number of electrons per reaction, F is the Faraday constant, A_s is the surface area of the particle, and R_s is the radius of the particle. Model-based methods offer several advantages. They provide a detailed understanding of the battery's internal processes, which can lead to more accurate SoC estimation. These models can also be adapted to account for various factors such as temperature, aging, and different operating conditions. However, they require extensive parameterization and validation, which can be complex and time-consuming. In practice, model-based methods are often combined with estimation algorithms such as the Kalman Filter to improve accuracy and robustness. The Kalman Filter uses a recursive approach to estimate the state of a dynamic system from a series of noisy measurements. It can be applied to the battery model to continuously update the SoC estimate based on the measured terminal voltage and current [49]. In summary, model-based methods are powerful tools for SoC estimation due to their ability to accurately represent the battery's behavior. While they require significant effort to develop and validate, their accuracy and adaptability make them a valuable component of advanced battery management systems.

7.4. State Observer Methods

The Kalman Filter (KF) and its variants are powerful tools for estimating the state of charge (SoC) of lithium-ion batteries due to their ability to handle noise and uncertainties in the measurement process. The basic Kalman Filter is a recursive algorithm that estimates the state of a dynamic system from a series of noisy measurements [50]. It consists of two main steps: prediction and update. The state-space model for the battery can be described as:

$$x_{k+1} = Ax_k + Bu_k + w_k \tag{8}$$

$$y_k = Cx_k + v_k \tag{9}$$

where x_k is the state vector at time step k, u_k is the control input, y_k is the measurement vector, A is the state transition matrix, B is the control input matrix, C is the measurement matrix, w_k is the process noise, and v_k is the measurement noise. The process noise w_k and measurement noise v_k are assumed to be Gaussian with zero mean and covariance matrices Q and R, respectively. The Kalman Filter algorithm consists of the following steps:

1. Prediction:

$$\hat{x}_{k|k-1} = A\hat{x}_{k-1|k-1} + Bu_k \tag{10}$$

$$P_{k|k-1} = AP_{k-1|k-1}A^T + Q \tag{11}$$

2. Update:

$$K_k = P_{k|k-1}C^T(CP_{k|k-1}C^T + R)^{-1} \tag{12}$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(y_k - C\hat{x}_{k|k-1}) \tag{13}$$

$$P_{k|k} = (I - K_kC)P_{k|k-1} \tag{14}$$

The Extended Kalman Filter (EKF) is a nonlinear extension of the Kalman Filter, which linearize the state and measurement equations around the current estimate [51]. The Unscented Kalman Filter (UKF) further improves on the EKF by using a deterministic sampling technique to capture the mean and covariance estimates accurately [52]. The EKF algorithm involves the following steps:

1. Prediction:

$$\hat{x}_{k|k-1} = f(\hat{x}_{k-1|k-1}, u_k) \tag{15}$$

$$P_{k|k-1} = F_kP_{k-1|k-1}F_k^T + Q \tag{16}$$

2. Update:

$$K_k = P_{k|k-1}H_k^T(H_kP_{k|k-1}H_k^T + R)^{-1} \tag{17}$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(y_k - h(\hat{x}_{k|k-1})) \tag{18}$$

$$P_{k|k} = (I - K_kH_k)P_{k|k-1} \tag{19}$$

where f and h are the nonlinear state transition and measurement functions, and F_k and H_k are the Jacobians of f and h with respect to the state. The UKF uses a set of sigma points to approximate the state distribution. These sigma points are propagated through the nonlinear functions, and the mean and covariance of the state are then reconstructed from the propagated sigma points. The Kalman Filter and its variants provide high-quality SoC estimates due to their ability to handle noise and model uncertainties. They are particularly effective in dynamic environments where the battery's operating conditions change rapidly. However, these methods also have computational drawbacks. The matrix operations involved in the prediction and update steps can be computationally intensive, making real-time implementation on embedded systems challenging. The EKF and UKF, in particular, require the computation of Jacobians and sigma points, respectively, which adds to the computational burden. In summary, while the Kalman Filter and its variants offer accurate and robust SoC estimation, their computational complexity can be a significant drawback for real-time embedded systems typical of battery management systems. Careful optimization and efficient implementation are necessary to leverage their benefits in practical applications. Other state observer-based methods include the Luenberger Observer and the Sliding Mode Observer (SMO). The Luenberger Observer is a linear observer that estimates the state of a system by correcting the predicted state with the measurement error [53]. It is simpler and computationally less intensive than the Kalman Filter but may not handle non-linearities and noise as effectively. The Sliding Mode Observer, on the other hand, is robust to model uncertainties and disturbances. It uses a discontinuous control law to drive the estimation error to zero, making it suitable for systems with high levels of uncertainty and noise. However, the SMO can introduce chattering, which may require additional smoothing techniques [54].

7.5. Machine Learning and Artificial Intelligence Models

Machine Learning (ML) and Artificial Intelligence (AI) methods are increasingly being used for state-of-charge (SoC) estimation due to their ability to model complex, nonlinear relationships without requiring detailed physical models of the battery. These methods include techniques such as Support Vector Regressors (SVRs), k-nearest neighbors (k-NN), random forests, and various types of neural networks, including artificial neural networks (ANNs), convolutional neural networks (CNNs), and long short-term memory (LSTM) networks [55,56]. ML and AI-based methods typically involve three main steps: data collection and preparation, model training, and model evaluation. Data collection involves gathering a large dataset of battery operating parameters, such as voltage, current, temperature, and historical SoC values. These data are then preprocessed to remove noise and normalize the values. During model training, the preprocessed data are used to train the ML or AI model to learn the relationship between the input parameters and the SoC. Finally, the trained model is evaluated using metrics such as the R-squared score, mean absolute error (MAE), and root mean square error (RMSE) to ensure its accuracy and robustness [57]. One of the most commonly used ML techniques for SoC estimation is the Support Vector Regressor (SVR). The SVR aims to find a function that deviates from the actual observed values by a value no greater than a specified margin, while also being as flat as possible. The optimization problem for SVR can be formulated as:

$$\min_{\mathbf{w},b,\xi,\xi^*} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{20}$$

subject to

$$y_i - (\mathbf{w} \cdot \phi(\mathbf{x}_i) + b) \leq \epsilon + \xi_i \tag{21}$$

$$(\mathbf{w} \cdot \phi(\mathbf{x}_i) + b) - y_i \leq \epsilon + \xi_i^* \tag{22}$$

$$\xi_i, \xi_i^* \geq 0 \tag{23}$$

where $\mathbf{w}$ is the weight vector, b is the bias term, ξ_i and ξ_i^* are slack variables, C is the regularization parameter, ϵ is the margin of tolerance, $\mathbf{x}_i$ are the input features, and y_i are the target values. Neural networks, particularly LSTM networks, are also widely used for SoC estimation. LSTM networks are a type of recurrent neural network (RNN) that can capture long-term dependencies in sequential data [58]. The LSTM cell is defined by the following equations:

$$\begin{aligned}
f_t &= \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\
i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\
\tilde{C}t &= \tanh(W_C \cdot [ht-1, x_t] + b_C) \\
C_t &= f_t \cdot C_{t-1} + i_t \cdot \tilde{C}t \\
o_t &= \sigma(W_o \cdot [ht-1, x_t] + b_o) \\
h_t &= o_t \cdot \tanh(C_t)
\end{aligned} \tag{24}$$

where f_t is the forget gate, i_t is the input gate, $\tilde{C}_t$ is the candidate cell state, C_t is the cell state, o_t is the output gate, h_t is the hidden state, x_t is the input at time step t, and W and b are the weight matrices and bias vectors, respectively. ML and AI-based methods offer several advantages for SoC estimation. They can handle the nonlinear and time-varying nature of battery behavior and adapt to different battery chemistries and operating conditions without requiring extensive reparameterization. These methods can achieve high accuracy, with typical errors in SoC estimation being within a few percentage points. However, they require large amounts of data for training and can be computationally intensive, making real-time implementation on embedded systems challenging. Techniques such as model compression, quantization, and hardware acceleration can help mitigate these issues and enable the deployment of ML and AI models in battery management systems. Interpretability is a critical aspect in automotive applications, where understanding the decision-making process of the model is essential for safety and regulatory compliance. Interpretable ML models, such as decision trees and linear models, provide clear and understandable relationships between input features and the SoC estimate. However, more complex models, like neural networks, often act as "black boxes", making it difficult to interpret their outputs. Techniques such as SHAP (SHapley Additive exPlanations) values and LIME (Local Interpretable Model-agnostic Explanations) can be used to provide insights into the model's decision-making process by explaining the contribution of each input feature to the final prediction. In summary, ML and AI-based methods offer a promising approach for SoC estimation due to their flexibility and ability to model complex relationships. However, their computational requirements and dependence on high-quality training data must be carefully managed to ensure reliable performance in practical applications. Additionally, ensuring the interpretability of these models is crucial in automotive applications to meet safety standards and regulatory requirements.

7.6. Integrated Circuits for EIS-Based BMS and Battery State Estimation

As already mentioned in the previous sections, the use of Electrochemical Impedance Spectroscopy (EIS) for state estimation measurements offers a powerful complement to established methods like Coulomb Counting and OCV monitoring [59,60]. EIS is particularly suitable for automotive applications due to its ability to provide detailed insights into battery health and performance. While many EIS studies still rely on cumbersome, costly, and power-intensive laboratory equipment, there is a growing interest in developing compact hardware and algorithms for online EIS, allowing impedance measurements to be conducted directly on batteries during use or charging. One effective method for online EIS involves modulating the DC-DC converter of the battery charger to generate the necessary perturbations for impedance measurement [61,62]. Although systems based on this concept do not need to be particularly compact since only one unit is needed for an entire battery pack, they do provide a global impedance measurement, which is less effective for monitoring individual cells. In contrast, devices designed for EIS on individual cells or small groups within a large battery pack must be compact and ideally powered by the cells they monitor. A key challenge is achieving impedance measurements with a resolution below 1 mΩ for cells with capacities around a few Ah. The literature offers few examples that meet these criteria. For instance, the work of De Angelis et al. [63] showcases a circuit on a relatively compact printed circuit board (PCB) with notable performance; however, it still requires a power source with a voltage higher than the cell under test, along with commercial data acquisition systems not included on the PCB. The authors in [64] propose a stand-alone BMS with EIS capabilities, but it also requires an auxiliary 6 V battery for power. The original system discussed in [65] employs an Application Specific Integrated Circuit (ASIC) to minimize size, but its performance seems adequate only for small button cells, where high output resistance eases resolution requirements. Gong et al. [66] also propose an ASIC for a promising single-cell supervisor that can be easily stacked for monitoring series-connected batteries; however, their experiments are limited to hybrid systems that rely on large external hardware. Recently, a compact online multi-cell measurement system was proposed in [67,68] with the capabilities of measuring standard parameters such as the SoC and SoH but also the possibility of reading additional parameters (e.g., the battery voltage, and interfacing external sensors) to complete the battery characterization. Such systems rely on a versatile general-purpose sensor interface capable of performing EIS with dimensions of only 1.5 × 1.5 mm^2, called SENSIPLUS [69]. This approach paves the way for the realization of online BMS networks that can provide more comprehensive battery monitoring while minimally impacting the space footprint, making EIS a highly suitable method for automotive applications.

7.7. Comparison of SoC Estimation Methods

In this section, we compare various methods for estimating the state of charge (SoC) of lithium-ion batteries. The comparison is based on metrics such as the estimation accuracy, computational complexity, and suitability for real-time embedded systems. The methods considered include Coulomb Counting, Open-Circuit Voltage (OCV), Kalman Filter (KF) and its variants, Machine Learning (ML) and Artificial Intelligence (AI) models, and Electrochemical Impedance Spectroscopy (EIS).

- The Coulomb Counting method is straightforward and computationally efficient, making it suitable for real-time applications. However, it suffers from cumulative errors and requires accurate initial SoC knowledge. Its accuracy can be improved by combining it with other methods like Kalman Filtering.
- The Open-Circuit Voltage (OCV) method provides accurate SoC estimates when the battery is at rest. It is computationally simple but requires the battery to be disconnected from any load or charging source for a period, which can be impractical. The method is often used in combination with other techniques to improve accuracy and reliability.
- Kalman Filter and Variants (KF) and its variants, such as the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF), offer high-quality SoC estimates by handling noise and model uncertainties effectively. These methods are particularly useful in dynamic environments but are computationally intensive, making real-time implementation on embedded systems challenging.
- Machine Learning and Artificial Intelligence Models, including Support Vector Regressors (SVRs), neural networks, and LSTM networks, can model complex, nonlinear relationships and adapt to different battery systems and conditions. They achieve high accuracy but require large amounts of training data and significant computational resources. Techniques like model compression and hardware acceleration can help integrate these models into embedded systems. Interpretability is crucial in automotive applications, and techniques like SHAP values and LIME can provide insights into the model's decision-making process.
- The Electrochemical Impedance Spectroscopy (EIS) method offers detailed insights into the battery's internal state by measuring its impedance across a range of frequencies. EIS can provide accurate SoC estimates and additional information about the battery's health (SoH). While traditionally requiring complex and power-intensive equipment, advancements in compact hardware and algorithms are making EIS more feasible for real-time applications. However, it remains computationally intensive and may require specialized hardware for integration into embedded systems.

The Coulomb Counting method is simple and efficient but prone to cumulative errors. The OCV method is accurate under stable conditions but requires the battery to be at rest. Kalman Filter and its variants provide robust estimates but are computationally intensive. ML and AI models offer the highest accuracy and adaptability but require significant computational resources and large datasets for training. EIS provides detailed insights and high accuracy but requires specialized hardware and can be computationally demanding. Table 8 shows a comparison among different SoC estimation methods.

In conclusion, the choice of SoC estimation method depends on the specific requirements of the application, including the need for accuracy, computational resources, and real-time capabilities. Combining multiple methods can often provide a balanced solution, leveraging the strengths of each approach.

Table 8. Comparison of SoC estimation methods.

Method	Accuracy	Computational Complexity	Real-Time Suitability	Interpretability
Coulomb Counting	Average	Very Low	Very High	High
OCV	Average/High	Low	High	High
Kalman Filter	High	Average/High	Average	High
ML/AI Models	High	Average/Low	Average/High	Low for AI; Average for ML
EIS	High	High	Average	High

8. EV/HV Commercial Solutions

The commercial lithium-ion battery systems for electric and hybrid vehicles showcase a diverse range of technologies, each tailored to specific performance requirements, cost considerations, and safety standards. Tesla's Model S, a benchmark in electric vehicle technology, employs a high-voltage 400 V architecture with Nickel-Cobalt-Aluminum (NCA) cylindrical cells. These cells deliver high energy density (150–200 Wh/kg), making them ideal for long-range electric vehicles (EVs). Tesla integrates a sophisticated Battery Management System (BMS) that includes features such as overcurrent and overvoltage protection, ensuring operational safety. The system also employs liquid cooling to maintain optimal thermal conditions, a critical feature given the high energy output and charging speeds. For state-of-charge (SOC) estimation, Tesla combines Coulomb Counting for continuous monitoring and Kalman Filter methods for correcting errors dynamically, providing accurate and reliable estimates even under variable load conditions. BMW's i3 and Audi's e-tron rely on Nickel-Manganese-Cobalt (NMC) prismatic cells, with voltages of 350 V and 400 V, respectively. These configurations offer a balance between energy density and thermal stability, chosen for their premium yet compact EV designs. Both manufacturers adopt advanced BMS technology, featuring liquid cooling systems to ensure consistent performance and mitigate risks of thermal runaway during high-load scenarios. Safety measures in these systems include redundant temperature and voltage monitoring, making them robust for extended use. Nissan's Leaf and Chevrolet's Bolt EV adopt moderate-cost NMC prismatic cell systems, operating at 360 V and 350 V, respectively. These vehicles strike a balance between cost and performance, targeting the mass-market segment. The integrated BMS in both systems incorporates air cooling, which, while less efficient than liquid cooling, reduces manufacturing complexity and cost. SOC estimation combines Open-Circuit Voltage (OCV) for static state measurements and Coulomb Counting for dynamic operation, ensuring a practical trade-off between accuracy and affordability. Toyota's Prius, a leader in the hybrid vehicle market, features a 200 V Nickel-Metal Hydride (NiMH) prismatic system. This low-cost architecture emphasizes durability and simplicity over energy density, aligning with the hybrid's auxiliary battery role. The Prius relies on a basic BMS equipped with air cooling, prioritizing robustness and minimal maintenance, which are critical for long-term reliability in hybrid applications. Ford's Fusion Energi, a plug-in hybrid, utilizes a 300 V NMC prismatic cell system with integrated BMS. The inclusion of air cooling in this system demonstrates a focus on cost-efficiency while maintaining adequate thermal management for typical hybrid use cases. This configuration is optimized for medium-range performance and affordability, reflecting its role in the hybrid vehicle segment. Hyundai's Kona Electric and Jaguar's I-PACE employ 400 V NMC pouch cell architectures, which prioritize high energy density and compact form factors. These vehicles integrate advanced BMS with features like liquid cooling to handle high power outputs and mitigate thermal risks. For SOC estimation, they adopt Kalman Filters, which provide superior accuracy under dynamic driving conditions, ensuring reliability and efficiency. Kia's Soul EV features a 375 V NMC pouch cell system with a BMS that utilizes air cooling and OCV-based SOC estimation. This system focuses on balancing performance with cost-effectiveness, targeting consumers seeking affordable yet reliable EVs. Each of these systems reflects the nuanced approaches manufacturers take to optimize battery performance, safety, and cost-effectiveness. High-performance models like the Tesla Model S and Jaguar I-PACE prioritize advanced cooling systems and cutting-edge SOC estimation techniques to maximize range and reliability. Conversely, mass-market and hybrid vehicles like the Nissan Leaf and Toyota Prius prioritize durability and cost savings, often opting for simpler thermal management and BMS architectures. These solutions illustrate the diversity of design philosophies in the EV industry, where the choice of battery chemistry, form factor, cooling mechanism, and SOC estimation method reflects each manufacturer's specific priorities and target market. This comparative analysis highlights the strategic trade-offs that drive innovation and adoption in electric and hybrid vehicle battery systems, as detailed in references like Tesla Battery Technology, Nissan Leaf Technical Specifications, and Jaguar I-PACE Specifications. Table 9 resumes the different characteristics of commercial lithium-ion battery systems.

Table 9. Comparison of commercial lithium-ion battery systems for electric and hybrid vehicles.

Brand	Vehicle Model	Voltage Range	Power Range	Autonomy	Energy Density	Cost	SOC Algorithms
Tesla	Model S	350–400 V	200–310 kW	370–520 km	250–300 Wh/kg	High	KF [70]
Nissan	Leaf	350–360 V	110–160 kW	240–360 km	150–200 Wh/kg	Moderate	Coulomb Counting + OCV [71]
BMW	i3	350–360 V	125–170 kW	260–310 km	200–250 Wh/kg	High	Model-based [72]
Chevrolet	Bolt EV	350–360 V	150–200 kW	380–420 km	200–250 Wh/kg	Moderate	ML [73]
Toyota	Prius (Hybrid)	200–220 V	90–110 kW	800–1000 km (combined)	100–150 Wh/kg	Low	Coulomb Counting [74]
Ford	Fusion Energi (Plug-in Hybrid)	300–320 V	120–150 kW	40–50 km (electric)	150–200 Wh/kg	Moderate	EKF [75]
Hyundai	Kona Electric	350–400 V	150–170 kW	400–480 km	200–250 Wh/kg	Moderate	ANN [76]
Kia	Soul EV	350–375 V	110–150 kW	280–320 km	200–250 Wh/kg	Moderate	Adaptive KF [77]
Audi	e-tron	350–400 V	200–300 kW	350–400 km	200–250 Wh/kg	High	KF [78]
Jaguar	I-PACE	350–400 V	200–294 kW	400–470 km	200–250 Wh/kg	High	ML [79]

9. Inter-Sectorial Applications of Li-Ion Batteries

The use of lithium-ion (Li-ion) batteries has had a significant and growing impact in various sectors, not only in the automotive industry but also in highly specialized fields such as aerospace and satellite technology. The increasing adoption of Li-ion batteries is primarily due to their unique characteristics, which make them ideal for applications that require high energy density, lightweight design, longevity, and resistance to extreme operating conditions. This section explores the inter-sectorial applications of Li-ion batteries, highlighting how these technologies have become a cornerstone for multiple industries and how they contribute to energy efficiency and sustainability.

9.1. Aerospace Sector

In the aerospace industry [80], Li-ion batteries have become a crucial component due to their distinctive properties, which meet very specific needs. Space missions require power systems that are not only lightweight and compact but also capable of ensuring reliable performance over extended periods and under extreme environmental conditions.

Li-ion batteries, with their high energy density, are particularly well suited for meeting these demands.

- High Energy Density: Li-ion batteries can store a significant amount of energy in a reduced volume. In aerospace contexts, where space and weight are limited resources, this characteristic is essential for the design of spacecraft, rockets, and satellites.
- Long Lifespan: Li-ion batteries have a long cycle life, allowing them to support long-duration space missions, even those extending for years, such as satellites and probes.
- Reliability in Extreme Conditions: Space is an extremely inhospitable environment, with temperatures ranging from extremely low to very high, in addition to radiation and other conditions that test any electronic equipment. Li-ion batteries, due to their resilience and stability, are capable of operating even in these extreme environments without compromising safety or reliability.

9.2. Satellite Sector

In the satellite sector [81], the need for high-performance devices that can operate autonomously for extended periods is vital. Li-ion batteries, with their rapid charging capabilities, low self-discharge rates, and long lifespan, have become the heart of many modern satellite operations.

- Energy Efficiency: Li-ion batteries have higher charging efficiency compared to other technologies, allowing satellites to optimize solar energy usage during periods of sun exposure. This characteristic is critical for maximizing the duration of space missions, as solar energy is the primary power source for many satellites.
- Low Self-Discharge: A key feature for satellites that must maintain their charge over long periods, even when not exposed to direct sunlight, is low self-discharge. Li-ion batteries lose much less of their charge compared to other battery types, which is a significant advantage in space applications, where recharging is not feasible.

9.3. Integration with Other Sectors

Li-ion batteries, although primarily associated with aerospace and satellites, also find essential applications in other technological fields, some of which intersect with the global progress toward energy sustainability.

- Electric Mobility: Li-ion batteries have become a key technology in the transition to electric mobility, powering electric vehicles (EVs) that help reduce carbon emissions and air pollution. Their high energy density enables electric cars to travel long distances on a single charge, while fast-charging capabilities contribute to the overall efficiency of electric vehicle fleets. Furthermore, the adoption of these batteries in electric public transport systems, such as buses and trains, is playing a crucial role in decarbonizing urban transportation systems.
- Portable Technology: Li-ion batteries form the backbone of consumer electronic devices such as smartphones, laptops, and tablets. Thanks to their lightweight design, fast charging, and long lifespan, they significantly enhance user experience, allowing for more powerful devices with greater autonomy. Additionally, Li-ion batteries are also used in wearable devices, such as smartwatches and fitness trackers, which require compact and durable power sources. For such applications, the low power consumption is a mandatory feature, requiring dedicated circuits [82–84].
- Renewable Energy: Li-ion batteries are employed to store energy generated from renewable sources such as solar and wind power, playing a key role in managing the intermittency of these sources. Stored energy can be used when production is low, thus ensuring a continuous and stable power supply. In residential and commercial energy storage systems, Li-ion batteries also allow consumers to optimize their energy use, reducing reliance on traditional power grids.

The expansion of lithium-ion battery applications in the aerospace and satellite sectors, as well as in industries such as electric mobility, portable technology, and renewable energy, represents a fundamental evolution in the pursuit of more efficient and sustainable solutions. Li-ion batteries not only meet advanced technical requirements in extreme contexts but also play a key role in the global transition toward a greener future. The integration of knowledge about this technology across various industrial and scientific areas provides a broader view of its potential and the benefits it can bring in terms of efficiency, sustainability, and technological innovation.

10. Conclusions and Future Work

The transition to sustainable mobility is intrinsically linked to advancements in lithium-ion (Li-ion) battery technology, which currently stands as the most viable solution for electric vehicles (EVs) due to their high energy density, long cycle life, and scalability. The integration of sophisticated Battery Management Systems (BMSs) has further enhanced the safety, efficiency, and reliability of these batteries, rendering them indispensable in modern EV applications. Li-ion batteries are pivotal in reducing greenhouse gas emissions and dependence on fossil fuels. Their high energy density and long cycle life make them particularly suitable for automotive applications. However, the critical role of the BMS cannot be overstated. The BMS is essential for monitoring, controlling, and optimizing the performance of Li-ion batteries, ensuring safe operations and extending the batteries' lifespan. Key functions of the BMS include monitoring cell voltage, current, and temperature, balancing cells, and managing thermal conditions. The selection of materials for anodes, cathodes, electrolytes, and separators significantly impacts the performance, safety, and longevity of batteries. Cell formats, such as cylindrical, prismatic, and pouch, offer various advantages and disadvantages in terms of thermal management, mechanical resistance, and energy density. Designing battery packs for commercial vehicles necessitates balancing energy capacity, voltage, power, dimensions, and weight. Series and parallel cell connections are crucial for optimizing the desired characteristics of the battery pack. Disconnection systems and pre-charge circuits are fundamental for protecting batteries and electronic components during use and maintenance, enhancing overall system safety. Various methods, including Coulomb Counting, Open-Circuit Voltage (OCV), Kalman Filters, and Machine Learning models, offer different levels of accuracy and computational complexity for estimating the state of charge (SoC). The novelty of this review lies in its holistic approach, which not only consolidates the latest research on Li-ion batteries but also emphasizes the critical integration of advanced BMS functionalities tailored for automotive applications. These include thermal management systems, real-time cell monitoring, and adaptive SoC estimation algorithms. Furthermore, the discussion on compact and scalable solutions like Electrochemical Impedance Spectroscopy (EIS) for real-time diagnostics highlights cutting-edge trends in battery management. Looking to the future, while many emerging battery chemicals show promise, the primary focus of near-term innovation should remain on advancing BMS technologies to address the critical challenges associated with Li-ion batteries in EV applications. Future research should focus on refining BMS algorithms to improve safety and efficiency under extreme conditions, such as high current loads or rapid thermal variations. Another key area is enhancing modularity in BMS design, which would allow greater flexibility and compatibility across various EV platforms. The development of adaptive algorithms for SoC and state-of-health (SoH) estimation will enhance the robustness of BMS under dynamic and extreme operating conditions. Lastly, the integration of compact and efficient EIS-based diagnostic tools into standard BMS platforms holds promise for more precise monitoring of individual cells and improved safety outcomes. Additionally, efforts should be directed toward exploring advanced thermal management techniques tailored specifically for BMS in automotive applications. This includes active cooling systems and innovative materials for heat dissipation to mitigate risks of thermal runaway. Another area deserving attention is the integration of Machine Learning models in BMSs to enhance predictive maintenance and optimize battery life-cycles. Such advancements will ensure that BMS technologies continue to act as a linchpin in the push toward sustainable and efficient energy storage solutions.

Extending this review work to other applications, such as aerospace and satellites, could prove extremely valuable. Li-ion batteries are already used in these applications for their high energy density and reliability. However, the specific needs of these sectors, such as advanced thermal management and resistance to extreme conditions, require further research and optimization. For example, in aerospace, batteries need to be lightweight, safe, and capable of operating over a wide temperature range. Research could focus on advanced materials and thermal management systems to improve safety and efficiency. In satellites, batteries must withstand high radiation levels and frequent charge/discharge cycles. Using innovative materials and advanced management techniques could enhance the durability and reliability of batteries under these extreme conditions. In conclusion, while lithium-ion batteries and their associated BMS technologies currently represent the most practical and scalable solutions for EV applications, their continued development remains critical to addressing existing limitations. By investing in advanced BMS functionalities, automotive systems can achieve superior safety, reliability, and efficiency. Extending this research to other sectors such as aerospace and satellites could lead to further improvements and innovative applications, paving the way for more efficient and sustainable energy storage solutions in the future.

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Acronyms and Symbols

Acronym	**Description**
EV	Electric Vehicle
BMS	Battery Management System
SOC	State of Charge
SOH	State of Health
NMC	Nickel Manganese Cobalt
NCA	Nickel Cobalt Aluminum
LFP	Lithium Iron Phosphate
OCV	Open-Circuit Voltage
EIS	Electrochemical Impedance Spectroscopy
PCB	Printed Circuit Board
ASIC	Application-Specific Integrated Circuit
ANN	Artificial Neural Network
LSTM	Long Short-Term Memory
KF	Kalman Filter
EKF	Extended Kalman Filter
UKF	Unscented Kalman Filter
SVR	Support Vector Regressor
ML	Machine Learning
AI	Artificial Intelligence

Symbol/Formula	**Description**
$LiCoO_2$	Lithium Cobalt Oxide
$LiFePO_4$	Lithium Iron Phosphate
$Li_4Ti_5O_{12}$	Lithium Titanate
$LiPF_6$	Lithium Hexafluorophosphate
V_{batt}	Battery Voltage
I_{batt}	Battery Current
C_{nom}	Nominal Capacity
$SoC(t)$	State of Charge at Time t
OCV	Open-Circuit Voltage
R_0	Internal Resistance
V_{RC}	Voltage across the RC Network
D_s	Diffusion Coefficient
c_s	Concentration of Lithium Ions in the Solid Phase
n	Number of Electrons per Reaction
F	Faraday Constant
A_s	Surface Area of the Particle
R_s	Radius of the Particle

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