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Review

Survey on Battery Technologies and Modeling Methods for Electric Vehicles

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Abstract: The systematic transition of conventional automobiles to their electrified counterparts is an imperative step toward successful decarbonization. Crucial advances in battery storage systems (BSS) and related technologies will enable this transition to proceed smoothly. This requires equivalent developments in several interconnected areas, such as complete battery cycles and battery management systems (BMS). In this context, this article critically examines state-of-the-art battery technologies from the perspective of automakers, provides insightful discussions, and poses open questions with possible answers. The generations of BSS (traditional, current, and futuristic) are first reviewed and analyzed via two distinct qualitative factors (DQFs): key design markers and performance indicators. Based on the introduced DQFs, major development trends and probable evolutions are forecasted. Thereafter, recent modeling and state estimation methods are comprehensively reviewed in relation to high-performance BMS. Accordingly, promising modeling methods are identified as futuristic solutions, leading to an accurate and timely decision for reliable and safer user experience. This article is concluded by presenting a techno-economic assessment of what to expect, as well as highlighting future challenges and opportunities for industry, academia, and policy makers.

Keywords: electric vehicles; battery technologies; battery management; modeling methods; key trends

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1. Introduction

The transportation sector is responsible for a considerable portion of unwanted greenhouse gas (GHG) emissions as well as global energy consumption, a fact evident from Figure 1 [1]. Therefore, policy makers are advocating for appropriate revisions of conventional automobiles to realize a sustainable and clean society [2]. Accordingly, the following targets have been put in place: China will reduce their GHG emissions consecutively after 2030, about 50% of new vehicles will achieve zero emissions in the USA by 2030, and almost all vehicles will achieve zero emissions in Europe by 2035 [3–5]. The electrification of conventional automobiles is considered a promising solution that is already in the implementation phase, and is expected to ramp up even further, as indicated and endorsed by policy makers, industry, and academia [6,7].

Electrification as a terminology essentially refers to the partial or complete replacement of standard gasoline engines with their electrochemical counterparts, such as battery storage systems (BSS), supercapacitors, and hydrogen-powered fuel cell systems [8,9]. The overall objective is to attain the same power/energy density as conventional gasoline engines. As illustrated in Figure 2, fuel cells and supercapacitors are present at the two polar ends, independently providing the competitive specific power/energy, while batteries can potentially provide the best of both [10,11]. Batteries have, therefore, been a subject of intensive research over the past decade, as they can be designed to achieve an appropriate power/energy balance [12,13]. This is evident from the recent prominence of battery electric vehicles (BEVs), effectively coupling a BSS with an electric motor as the only source of propulsion [14].

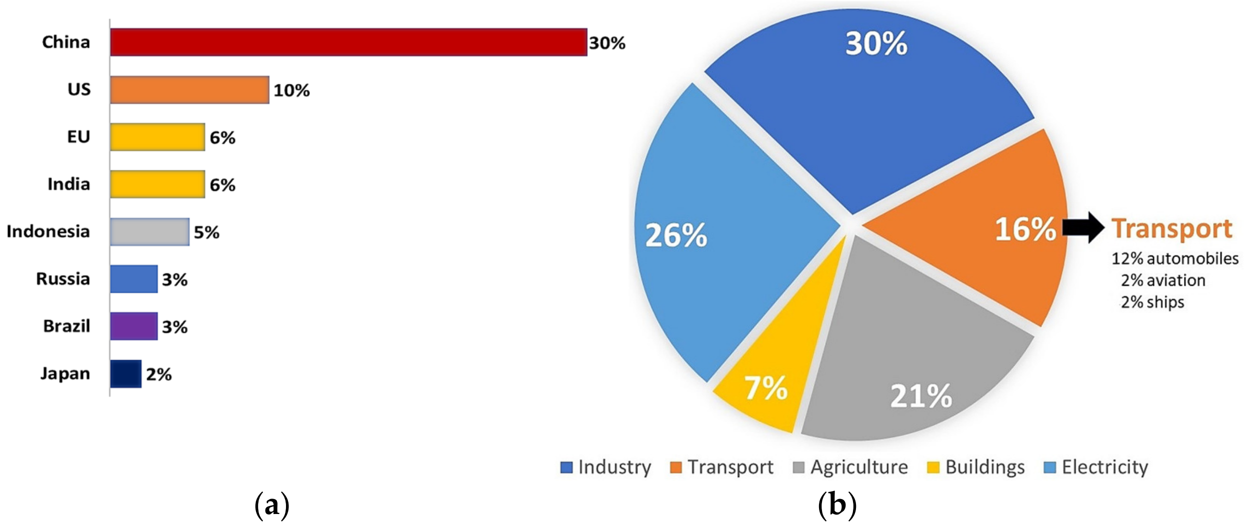


Figure 1. GHG emissions contributions⁺ (2020). (**a**) Country-wise. (**b**) Sector-wise. ⁺Data collected from Rhodium Group official webpage [1].

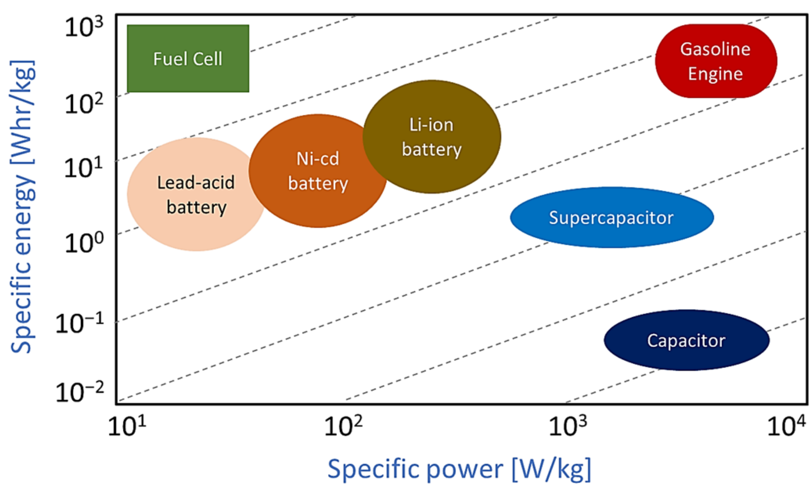
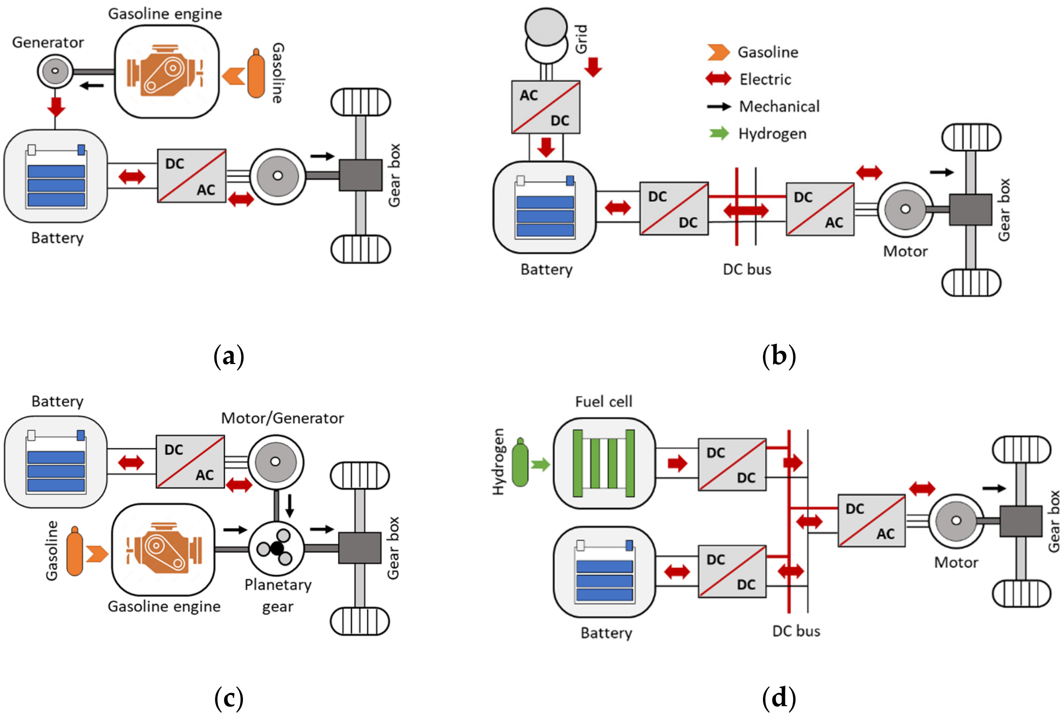


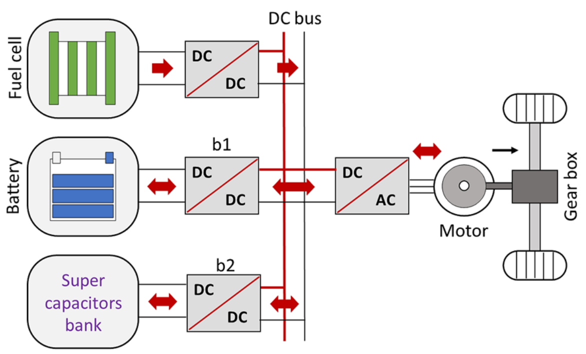
Figure 2. The specific power/energy of electrochemical sources.

Nevertheless, various well-proportioned combinations of electrochemical sources from Figure 3 (Part A) have already provided well-accepted and commonly available commercial products: gasoline hybrid electric vehicles (GHEV), range-extender hybrid electric vehicles (r-HEV), battery electric vehicles (BEV), and fuel cell hybrid electric vehicle (FCHEV) [15–18]. These products are identified by distinct merits in terms of commercial penetration, acceptance, and maturity, though the latter two (BEV and FCHEV) are the only true successors regarding complete electrification. It is worth mentioning here that the topologies presented in Figure 3 (Part A) do not correspond to an exhaustive list, but rather several possibilities can be viable both economically and performance-wise, as evident in the literature and elaborated comprehensively in Figure 3 (Part B).

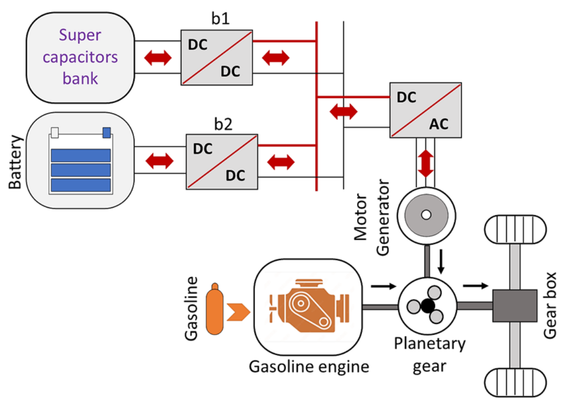
Part A: Well-accepted and commonly available commercial powertrain systems



Part B: Other powertrain possibilities well reported in the literature



FCHEV					
Type	FC	B	b1	SC	b2
S-Ac	✔	✔	χ	χ	χ
	✔	χ	χ	✔	χ
	✔	✔	χ	✔	✔
	✔	✔	✔	✔	χ
Ac	✔	✔	✔	✔	✔
All-electric					
Ac	χ	✔	✔	✔	✔
S-Ac	χ	✔	✔	✔	χ
	χ	✔	χ	✔	✔



GHEV				
Type	B	b2	SC	b1
S-Ac	✔	χ	✔	✔
	✔	✔	✔	χ
Ac	✔	✔	✔	✔

Figure 3. Powertrain configurations of electrified automobiles. (**a**) r-HEV (Nissan e-Power, etc.). (**b**) BEV (Renault Zoe, etc.). (**c**) GHEV (Toyota Prius, etc.). (**d**) FCHEV (Toyota Mirai, etc.). Legend: S-Ac (semi/active), FC (fuel cell), B (battery), SC (supercap), b12 (converters).

It can be observed from Figure 3 that BSS is an integral part of electrified automobiles in one way or another, such as in the case of FCHEV, where the battery system assists the fuel cell for comprehensive, effective, and efficient vehicular operation [19]. Naturally, the role of BSS in maintaining the overall performance of electrified automobiles is of paramount importance, whether it be in terms of power delivery, ownership price, travelling range, or comfort and safety [20]. Therefore, it is essential to improve and innovate several techno-economic aspects associated with battery technologies, including complete battery cycle [21,22], sustainable battery charging infrastructure [23,24], battery management system [25,26], etc.

Battery storage as a technology has enjoyed a profound evolution, with an impact that has matured over a century, and is still a topic of extensive research. The invention of the first rechargeable lead-acid battery by French physicist Gaston Plante in the late 19th century triggered the era of electrochemical storage devices [27,28]. This was followed by an unprecedented expansion, as several families of batteries for EVs were conceptualized and developed. However, from the perspective of automobiles, two distinct batteries, nickel metal hydride and lithium-ion, have gained massive popularity, and thus have been and still are widely employed in commercial electric vehicles (EVs) [29–32]. Currently, lithium-ion technology is the preferred choice for automotive manufacturers and dominates the EV industry owing to its obvious merits and high performance [33,34].

Most of the lithium-based batteries require precious and strategic minerals such as lithium itself together with cobalt [35]. Not only are these minerals becoming very expensive due to unprecedented demand, but the access to these minerals is becoming challenging because of current political turmoil [36,37]. A recent example is the political situation in the Democratic Republic of the Congo (production of more than 70% of the world's cobalt), which has significantly reduced cobalt's supply. Another problem is related to the mining, processing, and recycling of these minerals (lithium and cobalt) for battery use, as the whole process can be detrimental for the sustainable energy cycle. These challenges are motivating researchers and institutes to limit the usage of strategic minerals for batteries [37]. Subsequently, extensive research on the development of alternate technologies and the future generation of high-performance batteries is underway for electrified automobiles [38]. The key to future generation is exploiting the minerals with innate abundancy, least toxicity, and enhanced safety (such as sodium, sulfur, zinc, manganese, iron, aluminum, etc.) then assembling them in innovative ways to achieve high-performance electrochemical storage systems. Therefore, it is expected that several technological breakthroughs may emerge soon in the context of the future generation of batteries for electric automobiles [39–42].

Battery management and power control (elements of BMS) are considered integral and obligatory parts of BSS, especially for automobile applications. BMS ensures the reliable and safe operation of EV batteries and, therefore, overall stable vehicular operation. It is also of utmost importance, as the battery pack is usually the most expensive single component of EV, accounting for at least 35–45% of total manufacturing cost [43]. The power controller being a part of BMS regulates power/control-related problems such as monitoring the charging process via an external charger. The power controller operates according to information provided by the battery management unit including battery states (charge SoC, health SoH, temperature SoT, power, remaining useful life, etc.). BMS as a complete unit performs a series of functions, including (but not limited to) the following: (i) battery state estimation, (ii) battery cells balancing, (iii) battery charge/discharge control, (iv) thermal management, (v) communication, (vi) safety warnings, protection measures, and bidirectional human–media interaction, etc. [44–47].

In the context of BMS, discussion about state-of-the-art battery modeling and state (charge/health) estimation techniques is inevitable. The objective is to provide a virtual yet effective imitation of battery electrochemical behavior, with a good compromise between accuracy, ease of implementation, and flexible integration. If properly managed, it greatly assists in executing accurate and timely decisions, resulting in enhanced vehicular performance and extending the lifespan of battery storage [48,49]. In general, battery modeling methods are classified as: electrical (equivalent circuit), electrochemical, data-driven, etc. [50–53]. Battery state estimation has a close affinity with battery modeling techniques, as it is regarded as the expected outcome of battery modeling. State estimators are among the most important components of BMS for EV applications, since accurate and timely estimation is essential for reliable and safe operation of battery packs. The estimated states mainly include SoC, SoH, temperature, etc. Owing to its importance, the topic of battery state estimation is well reported and rigorously studied by several researchers [54–57]. Based on the provided literature, battery state estimators are typically categorized as follows: (i) simplistic [58–60]; (ii) filters [61,62]; and (iii) data-driven [63,64].

As electrified automobiles are the key future technologies for achieving the envisioned goal of sustainability and decarbonization, it is of utmost importance to study relevant technologies such as battery storage systems and associated management units from the perspective of automakers. This motivates a thorough techno-economic assessment and in-depth discussions, while leading to the identification of essential challenges, opportunities, and developments that can be expected and are crucial in the coming future.

2. Highlights and Contributions

The previous discussion clearly highlights the role of batteries and associated technologies in the ongoing success and future direction of electrified automobiles. Given the importance of this topic, it is critical to review these technologies and determine future directions, which can help academia, industry, and automakers. In general, finding the perfect battery chemistry is not easy, as it involves balancing several elements: safety, performance, cost, range, thermal profile, and reliability across the entire battery lifecycle. Several aspects of design, economics, and politics are related to this field, such as finding, extracting, and using appropriate materials that are abundant, safe, and easy to access, provide better value and performance, etc.

There are several discussions and studies in the literature on topics including battery technologies [20,65], battery management [2,44], modeling [51,66], estimation [67,68], materials [38], thermal design [69], recycling [70], etc. Though automakers primarily develop and use their proprietary technology, it is mandatory to understand the complete battery cycle and relevant technologies from their perspective to provide essential information and identify key development trends. This aspect requires further attention. In its context, this article critically examines the latest and emerging battery technologies from the perspective of automotive manufacturers. The main highlights and contributions of this paper are as follows:

- State-of-the-art battery storage systems are classified according to their technical maturity, development timeline, and existing applications. Accordingly, the traditional generation includes lead-acid and nickel-based batteries, the current generation consists of lithium-based batteries, while the future generation encompasses batteries that are currently not mature enough but are expected to succeed previous generations. The future generation includes metal-ion, metal-air, solid-state, and sodium-beta batteries.
- The complete battery cycle is described from the perspective of automakers. Several interconnected aspects including manufacturing, application, and recycling are detailed. Based on this, two distinct qualitative factors are introduced: key performance indicators and design markers.
- The generation-wise evolution of batteries is comprehensively reviewed based on the introduced qualitative factors. This makes it possible to predict the development of relevant technologies and, consequently, to furnish the blueprint of technologies that are expected to flourish in the future.
- Contemporary and emerging methods for battery modeling and state estimation are discussed in detail with relevance to battery management and power control units. The methods discussed are then ranked and prioritized according to key next-generation

requirements: accuracy, computational load, scalability, resilience, implementation, maturity, etc.

- As a conclusion, the paper provides a detailed techno-economic assessment of what to expect, and highlights future challenges and opportunities for industry, academia, and policy makers. The overall contents are graphically presented in Figure 4.

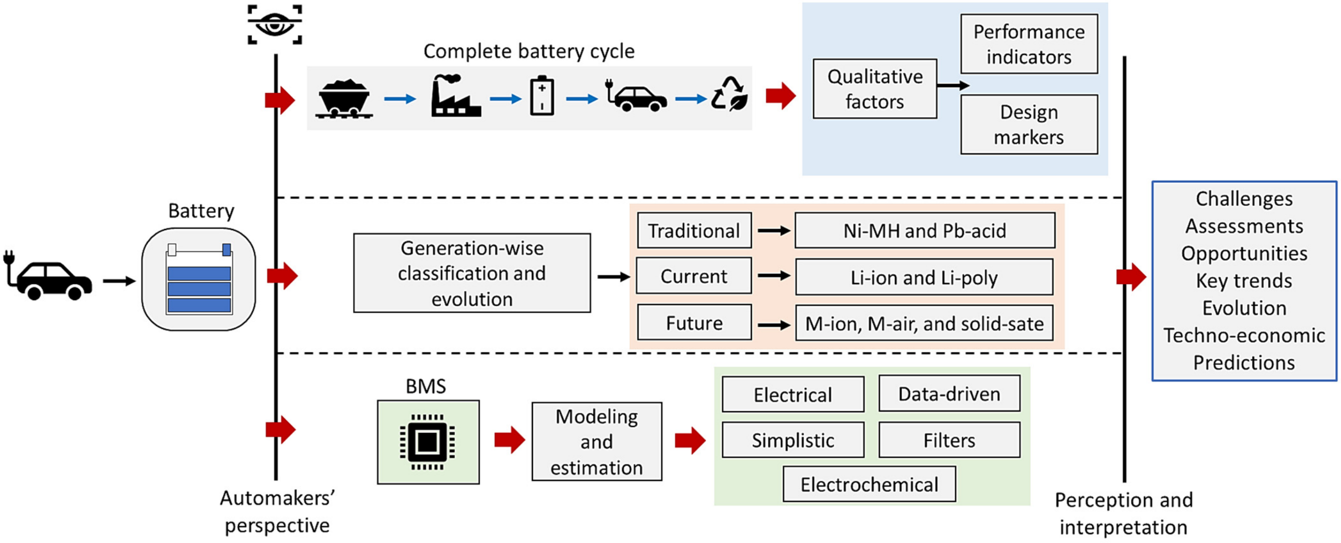


Figure 4. Contents and contributions of this article in a nutshell.

3. Battery Storage: Evolution and Key Trends

Before initiating the discussion on state-of-the-art battery types for electrified automobile, it is beneficial to understand the complete battery cycle from the perspective of automakers. A clear understanding can assist in introducing productive benchmarks to strategically position the BSS based on their distinct merits (pros and cons) as well as identifying associated challenges and opportunities, along with key future trends.

The complete battery cycle (manufacturing, application, and recycling) is a complicated process comprising several interrelated steps, as presented in Figure 5: material search and mining, transportation of raw materials to the manufacturing plant, processing of key minerals/materials, battery cell design, assembling the battery pack, integration of battery packs into the intended application, and, finally, recycling [71].

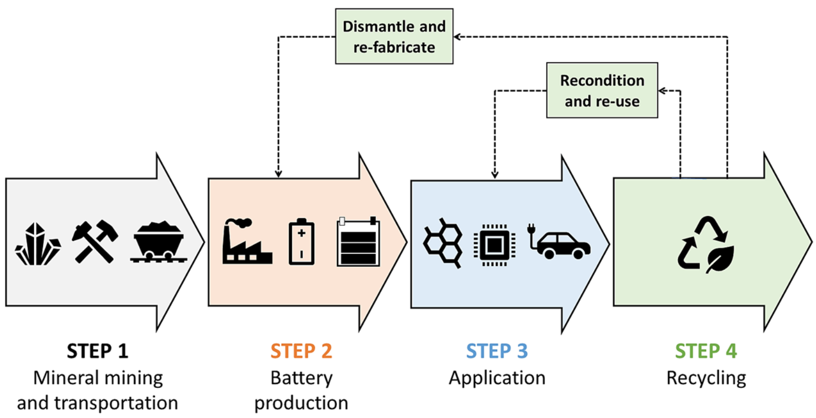


Figure 5. The complete battery cycle from the perspective of automakers.

The manufacturing cost of BSS for automobiles is a crucial factor, which is not only affected by the complete battery cycle, but also by the associated research and development. Even the fundamental purpose of BSS technology to support overall sustainable energy circle is affected by the complexity of complete battery cycle. The key minerals, which are rare, unsafe to use/recycle, and/or difficult to mine/process, can negatively impact the manufacturing price as well as disturb the sustainable energy circle.

There are two distinct qualitative factors (DQFs) to quantify the efficacy of the complete battery cycle in relation to the final product: (i) key performance indicators, such as lifetime, power (density and specific), energy (density and specific), efficiency, memory effect, etc., and (ii) design markers: cost, toxicity, abundancy, maturity, etc. The next generation of high-performance batteries for automotive applications is expected to provide a proper balance between these two qualitative factors.

In general, battery storage technologies can be broadly classified as follows: (i) The traditional generation consists of lead-acid and Ni-based batteries (pre-Lithium era). The batteries from the traditional generation are not preferred anymore for high-performance electrified automobiles. (ii) The current generation consists of Li-based batteries. The current generation has already superseded the traditional generation in terms of two qualitative indicators, and is the current preferred choice for a diverse range of EVs. (iii) The future generation is being extensively researched (post-Lithium era) and yet to manifest as a complete commercialized product at the same level as that of the current generation. The future generation is envisioned to offer unmatched performance in terms of key performance indicators as well as an appropriate balance between the introduced DQFs. However, the timely realization of intended outcomes is highly dependent on the direction of research for the future generation of batteries, as illustrated by recent research trends on EV batteries [36,72,73]. The future generation mainly encompasses metal-ion, metal-air, solid-state, and sodium-beta batteries. Accordingly, Figure 6 presents the graphical classification and generational evolution of battery types for EV and portable applications.

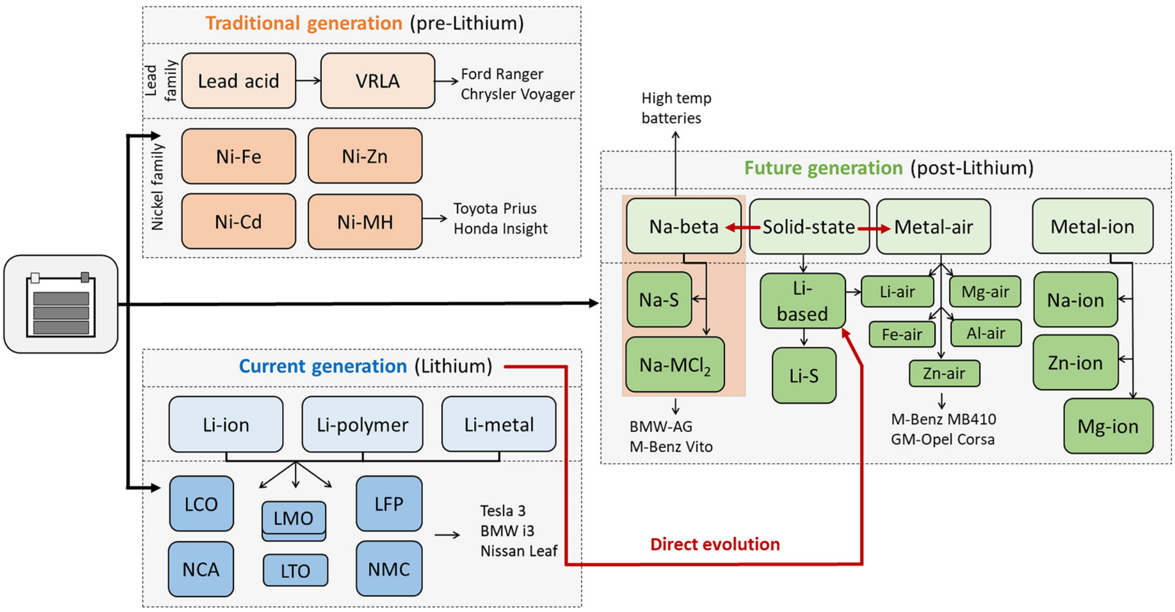


Figure 6. Generational evolution of batteries for EV applications.

The generation-wise evolution of battery technologies is comprehensively discussed in the subsequent sections. The discussion concludes with a comparison of key battery technologies that is effectively based on the introduced qualitative factors: key performance indicators (KPIs) and design markers (KDMs). The supporting data are collected from the literature [20,36,38,65,74], but presented in a unique and appropriate manner to facilitate the motivation and goals of this article. In this context, the first part of the comparison, which is about KPIs, is provided in Table 1, while the second part, about KDMs, is presented in Table 2.

Table 1. Comparison: key performance indicators of battery technologies. Here, the data are interpreted from the literature [20,36,38,65,74].

Battery Technologies			Key Performance Indicators					
Generation	**Family**	**Mention**	**Specific Energy (Wh/kg)**	**Specific Power (W/kg)**	**Cycles (×100)**	**Efficiency(%)**	**Memory Effect**	**Self-Discharge (%/Month)**
Traditional	Lead (Pb)-acid		L (30–50)	M (80–160)	L (3–5)	L (~75)	L	L-M
Traditional	Nickel-based	Ni-Cd	L (35–80)	M (120–150)	H (8–20)	L m (~80)	H	M-H
Traditional	Nickel-based	Ni-MH	M (60–120)	H (150–450)	M (3–15)	M (~85)	H	H
Current	Li-based	Li-ion (LFP)	H (120–200)	H (180–220)	VH (20–80)	H (~92)	VL	L
Current	Li-based	Li-ion (NMC)	H (150–220)	H (180–270)	H (20–25)	H (~94)	VL	L
Current	Li-based	Li-ion (LTO)	M (60–110)	~VH	VH (40–90)	VH (~95)	VL	VL
Current	Li-based	Li-poly (LCO)	H (120–220)	H (220–330)	H (10–22)	H (~92)	VL	L
Current	Li-based	Li-metal (LMO)	VH (250–360)	H (160–230)	~VH	VH (~95)	VL	VL
Future	Li-based	Solid-state (Li-S)	VH (~450)	~H	M (~15)	M-H (~87)	-	H
Future	Li-based	Solid-state (Li-O_2)	Ex (~5000)	~M	L (~5)	L (~75)	-	VL
Future	Metal-air	Zn-air (Zn-O_2)	VH (~450)	~M	M (3–10)	H (~90)	-	VL
Future	Na-beta	Na-S	H (115–200)	M (120–180)	H (8–30)	M (~85)	-	L-M
Future	Metal-ion	Na-ion	H (100–160)	~VH	H (5–20)	VH (~95)	VL	L

Legend: VL (very low), L (low), M (medium), H (high), VH (very high), Ex (exceptional/benchmark).

Table 2. Comparison: key design markers of battery technologies.

Battery Technologies			Key Design Markers						
Generation	**Family**	**Mention**	**Cost (EUR /kWh) §**	**Operating Range (°C)**	**Toxicity /Hazards**	**Overcharge Tolerance @**	**Abundance &/Mining**	**Recycling (Level)**	**Technical Maturity**
Traditional	Lead (Pb)-acid		L-M (~255)	A (−20–+45)	H/F/P/C	H	N/N-T	S (Cp)	H
Traditional	Nickel-based	Ni-Cd	M (~540)	A (0–+50)	H/P/C	M-H	N/N	S (Pa)	H
Traditional	Nickel-based	Ni-MH	~M-H	A (0–+50)	L/C	L-M	N/N	N (Pa)	M
Current	Li-based	Li-ion (LFP)	M (~425)	A (−20–+40)	L/F/C	L	N/N	N (Pa)	M
Current	Li-based	Li-ion (NMC)	H (~985)	A (−20–+50)	M/F$^+$/C	L	L/N-T	T (Pa)	M
Current	Li-based	Li-ion (LTO)	M-H (~625)	E (−40–+60)	L	L	L/N-T	T (Pa)	L-M
Current	Li-based	Li-poly (LCO)	~M-H	A (−20–+45)	M/F$^+$/C	L	L/N-T	T (Pa)	M
Current	Li-based	Li-metal (LMO)	~M	E (−40–+85)	L/F	-	N/N	-	L-M
Future	Li-based	Solid-state (Li-S)	~L-M	E (−20–+70)	L/C	L	H/N	T (Pa)	L
Future	Li-based	Solid-state (Li-O_2)	~L-M	E (−50–+90)	L/C	-	H/N	-	L
Future	Metal-air	Zn-air (Zn-O_2)	~L	E (−20–+70)	L/C	-	H/N	N (Pa)	L
Future	Na-beta	Na-S	~L	Ht (+270–+350)	L/F*/C	-	H/N	T (Pa)	L-M
Future	Metal-ion	Na-ion	~L	A (−20–+50)	L/F$^+$	L-M	H/N	T (Pa/Cp)	L-M

Legend: L (low), M (medium), H (high), A (ambient), E (extended), S (simple/established), N (normal/moderate), T (tough), Ht (high temperature), F (fire/explode), P (poison), C (chemical burn/corrosivity/fumes/pollution), Cp (complete), Pa (partial/incomplete). $^+$ Associated with organic solvents, which are highly inflammable, aside from the metallic element (at anode), which can catch fire if in contact with water; * associated with molten sodium and its residue materials, which, upon leakage, can cause short circuits; & indicate cumulative abundance of key minerals; @ charging beyond nominal capacity and with elevated charging rate; § standard, interpreted, and relative buying price as of 2022–23 by common vendors (CATL, CALB, etc.), plus the expected projections.

3.1. Traditional Generation of Batteries

Conventional batteries are representative of the pre-Lithium era, encompassing lead-acid and nickel-based batteries. Most of the conventional batteries are well established in terms of their technology, maturity, and applications.

3.1.1. Lead-Acid Batteries

The lead-acid family initiated the era of electrochemical batteries. The first lead-acid battery was conceptualized in 1859 by Gaston Plante in France. The lead-acid technology is distinguished by its maturity and lower manufacturing cost and has, therefore, dominated the market for over a century. In terms of composition, as exhibited in Figure 7a, lead (Pb) is used as the negative electrode, lead dioxide (PbO_2) is used as the positive electrode, and dilute sulfuric acid (H_2SO_4) is used as the electrolyte [75,76].

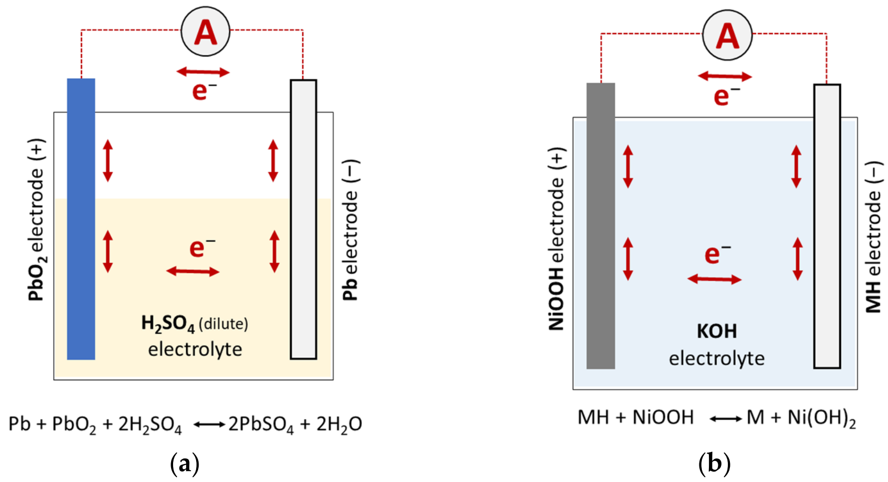


Figure 7. Composition of battery cell (traditional generation). (**a**) Lead-acid cell. (**b**) Ni-MH cell.

The specific energy and energy density of a typical lead-acid battery are relatively low. The cycle expectancy of lead-acid batteries is between 400 and 800, which is also on the lower side, especially for automotive applications. Moreover, lead being a toxic element means that it can be a burden to handle properly [77]. These drawbacks limit the use of lead-acid batteries to specific scenarios in automotive, such as starting, lighting, ignition, etc. [78].

Within the lead-acid family, the valve-regulated lead-acid battery (VRLA) is among the best options owing to significant advances in electrochemistry, resulting in higher specific energy/power and recharging speed [79,80]. The VRLA is a cumulative term accounting for gel cells and absorbed glass mat types. In addition, its intrinsic property of working well at both low and high temperatures renders it a potential candidate for EVs. With these attributes, VRLA batteries are used in some commercial vehicles as the main/starter energy source: Ford ranger, Chrysler Voyager, Suzuki Alto, etc. [20].

3.1.2. Nickel-Based Batteries

Nickel-based (Ni-based) batteries are also among the most-established electrochemical storage devices besides the lead-acid family. The first two Ni-based batteries (Ni-Fe and Ni-Cd) were invented by Waldemar Jungner in Sweden in 1899 [81]. Nickel as an element is superior to lead in terms of electrochemical properties and toxicity, but the typical cost of a Ni-based battery is substantially higher than that of a lead-acid one [82].

Within the Ni-based family, the Ni-Zn (nickel-zinc) battery has the highest nominal cell voltage (1.6 V) and is superior to its counterpart Ni-Cd battery in terms of non-toxicity and lower material cost [83,84]. However, the Ni-Zn battery still suffers from a short lifespan of around 300 cycles due to the partial solubility of zinc ions in the electrolyte [85]. This drawback limits the commercial utilization of Ni-Zn batteries for automotive applications, where the cycle expectancy should be higher. Another problem is the strong memory effect, which is a prominent problem in nickel-based batteries [86,87]. Consistently across Ni-based batteries, the cathode and electrolyte are, respectively, made of nickel oxyhydroxide (NiOOH) and potassium hydroxide (KOH), while the anode may differ depending on the type of battery (for example, in the case of Ni-Cd, the anode is cadmium) [88,89].

The Ni-metal-hydride battery (Ni-MH) is well embraced by automakers owing to its good performance indicators, moderate cycle expectancy, and proven technology [90,91]. The anode in the Ni-MH battery is composed of a metal-hydride alloy, which can absorb hydrogen [92]. The rest of the structure is the same as that of other Ni-based batteries.

The structure of a typical Ni-MH battery cell is exhibited in Figure 7b. The nominal cell voltage of the Ni-MH battery is on the lower side (1.32 V); however, both specific energy and energy density are superior to several Ni-based and lead-acid batteries [93]. Ni-MH batteries also have wide operating temperatures and are environmentally friendly. Given the clear merits, Ni-MH batteries are extensively used in several commercial EVs and hybrid electric vehicles (HEVs), such as Toyota Prius, Mirai, Honda Insight, Toyota RAV4L, etc. [20,94]. Currently, Ni-MH batteries, being the pinnacle of the Ni-based family, are being widely replaced by Li-based electrochemical devices due to their superior nature in almost all the key performance indicators.

3.2. Current Generation of Batteries

The current generation is focused on lithium-based (Li-based) batteries, which have superseded lead-acid and nickel-based batteries. This is particularly true for automotive and portable applications, as Li-based batteries are superior in terms of providing the same power/energy with much less volume/weight, no memory effect, low self-discharge, and a longer lifespan [38,95]. The research on Li-based electrochemical devices dates to 1912 (started by G.N. Lewis); however, a proper device was first conceptualized by Goodenough in the US in 1980 [96]. Later, the first working prototype was displayed in 1985 by Akira Yoshino in Japan [97], which then resulted in a commercial product by 1991 (SONY).

Li-based batteries can be subclassified into lithium-ion, lithium-ion polymer (quasi-metallic), and lithium-metal variants [20,38]. Polymer lithium batteries are considered a transition between current and future technologies, while Li-metal types are mostly the batteries of the future. Lithium-based batteries are already extensively used in several commercial EVs and HEVs, such as Tesla 3, BMW *i*3, Nissan Leaf, etc. [20].

3.2.1. Lithium-Ion Batteries

Currently, for electrified automobiles, Li-ion batteries are the preferred choice and, therefore, widely employed and considered a commercial success. This is thanks to their intrinsic superiority in terms of energy, safety, and lifetime compared to previous generations of conventional batteries. The Li-ion batteries with organic solvents are the most established, with competitive cost and high technical maturity. The anode of a typical Li-ion battery is made up of carbon or silicon-carbon, while the cathode is a layered metal oxide [38]. The electrolyte is usually a Li-salt (lithium hexafluorophosphate for good ionic conductivity and electrochemical stability) mixed in an organic solvent [98]. Depending on the material used for cathode design, the typical Li-ion batteries can be classified as LCO ($LiCoO_2$), NMC ($LiNiMnCoO_2$), and NCA ($LiNiCoAlO_2$) [99,100]. The NMC material provides a superior lifespan and better overall performance and, therefore, is preferable for automotive applications, while the NCA Li-ion battery is extensively used by Tesla in their electric cars. Another newer and popular variant is termed LTO (lithium-titanium-oxide), which differentiates itself by an anode made up of lithium-titanate nanocrystals instead of carbon, providing a much higher surface area per gram. This property enables higher power density for LTO type batteries (translating to fast charge/discharge), though, the open-circuit nominal voltage of the LTO battery is significantly reduced (~2.3 V), resulting in lower energy density compared to its counterparts (NMC, LCO, etc.). Nevertheless, most of the Li-ion batteries are flexible in terms of design; a trait from power/energy can be expanded at the cost of the other.

As cobalt can be regarded as one of the strategic and critical resources, considerable efforts are now devoted to finding alternate materials with a lesser percentage of cobalt. With this in mind, the Li-ion batteries are classified into three categories: cobalt-rich, cobalt-medium, and cobalt-free [20]. In this context, a contemporary variant of Li-ion batteries is LFP ($LiFePO_4$ as cathode material), which, despite having lower energy density, is becoming very popular for automotive applications due to its unsurpassed safety, high cycle life, and low cost (cobalt-free nature) [101]. Therefore, LFP is a suitable candidate for large-scale production for electrified vehicles. The composition of a typical LFP battery is presented in Figure 8a.

The commercialized Li-ion cells for EV applications are typically classified into three types: cylindrical, prismatic, and pouch type [38,102,103]. The cylindrical type is a steel shell package highly suitable for rapid and cost-effective manufacturing. Therefore, the cylindrical cell type has been favored by Tesla for almost all its early models. The prismatic cell is suitable for battery thermal management due to its cubic shape. In general, a large surface facilitates heat exchange between the cell and cooling source. As a result, prismatic cells are widely adopted by a variety of manufacturers such as Volkswagen, Toyota, Nissan, etc. The pouch type cells are still in the experimental stage due to associated safety concerns.

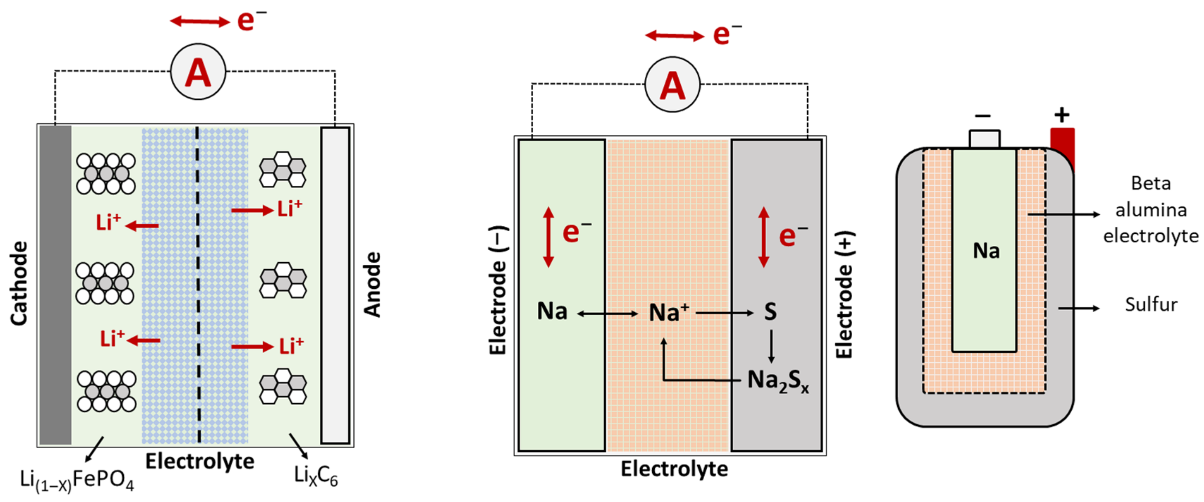


Figure 8. Composition of battery cell from current ((**a**): Li-ion LFP type cell) and future generation ((**b**): Na-S cell).

3.2.2. Lithium-Ion Polymer Batteries

The lithium-ion polymer (Li-poly) battery is a rechargeable type, employing a polymer electrolyte instead of the liquid electrolyte (Li-salt mixed in an organic solvent) of mainstream Li-ion batteries [104]. The rest of the structure is similar to Li-ion batteries, such as a transition metal-oxide $LiCoO_2$ used as the cathode (polymer LCO). The polymer electrolyte is typically a highly conductive semisolid gel, such as poly (ethylene oxide), poly(acrylonitrile), etc. [105]. Li-poly batteries provide higher specific energy, so are suitable for applications where weight is the deciding factor, such as portable devices [106].

Just like Li-ion batteries, Li-poly batteries operate according to the principle of the intercalation and de-intercalation of Li-ions between the positive and negative electrodes. Unlike Li-ion batteries' cylindrical and prismatic rigid casing, Li-poly batteries have flexible casing, which is somewhat resilient to external stresses [107]. The polymer-based electrolytes (quasi-metallic) deliver higher specific energy and power compared to aqueous types, but this feature comes with the compromise of overall higher manufacturing cost [38], which is the major deficiency of Li-poly technology. Li-poly batteries are considered a transition between the current and future generations of high-performance batteries.

3.2.3. Lithium-Metal Batteries

The lithium-metal (Li-metal) family is a relatively newer generation of batteries comprising different configurations, but all with metallic Li as the anode [108]. The Li-metal family is not mature enough from a commercial point of view and from the perspective of automakers, given the fact that most Li-metal batteries are still non-rechargeable (primary use) [109]. A popular and well-established Li-metal battery called the LMO battery uses metallic Li as the anode and manganese dioxide (MnO_2) as the cathode, along with Li-salt electrolyte in an organic solvent [109]. Such batteries provide a very high specific capacity of 3860 mAh/g, as evident from a coin-type LMO battery. The self-discharge is also low, with a longer lifespan and compact size (and light weight), but about 0.15–0.3 kg of Li/kWh is required, resulting in higher manufacturing costs. Therefore, such batteries are suitable for high-value and critical portable applications such as pacemakers and other medical devices [110,111].

Given their distinct merits, rechargeable Li-metal batteries are under rigorous research and development, as they have profound prospects for automotive and portable applications. Some researchers have proposed and investigated solid bio-polymer electrolytes to obtain higher energy density, an extended operating temperature range, and safety [112]. In 2018, a Li-metal polymer battery was commercially used in a hybrid electric vehicle for port operations with a wider temperature range of −20 to +65 (°C).

3.3. Future Generation of Batteries

As with other technologies, the current generation of Li-ion batteries will at some point of their technological lifespan reach the intrinsic limits of specific energy and energy density. Another important issue is the stringent necessity of key and strategic minerals (such as Li and Co) for high-performance Li-based batteries for EV applications. At present, the process of extracting and processing key minerals for Li-batteries is becoming increasingly difficult, which has a predominant impact on the overall manufacturing price of EVs and HEVs. Thus, these bottlenecks require battery technologies beyond lithium to be properly investigated. In this context, the 'future batteries' refer to novel technologies that are currently under development and have the potential to be the next-generation commercial batteries for automobiles. The future generation includes Na-beta, Na-ion, Metal-air, Li-metal (solid-state), etc. With the appropriate research and development focus, the 'future generation' should, over time, at least match (if not exceed) the 'current generation' in terms of key performance indicators, but with the added benefit of mineral abundance, environmental friendliness, and affordability.

3.3.1. Sodium-Beta Batteries

Sodium-beta (Na-beta) batteries are among the newest battery technologies and considered as a potential breakthrough, especially from the perspective of stationary applications [113,114]. The Na-beta family represents both solid-state and molten-state batteries, and they are considered a part of the future generation owing to raw material abundance and superior theoretical energy densities [20,38].

Presently, two technologies have been successfully realized: (i) sodium-metal chloride (Na-MCl_2) and (ii) sodium-sulfur (Na-S) [115,116]. The cathode of the Na-MCl_2 battery employs transition metal chlorides: the iron chloride (Na-$FeCl_2$) and nickel chloride (Na-$NiCl_2$). Out of these two types, the Na-$NiCl_2$ battery has the advantage of a wider operating temperature range, less metallic corrosion, and higher power density. Na-$NiCl_2$ batteries are employed in a couple of commercial vehicles, such as BMW-AG and Mercedes-Benz Vito [20]. This is because such batteries have superior energy densities, adequate cycling capability, and high operating efficiency [38]. However, cost is an important factor, which is related to the presence of nickel in the Na-$NiCl_2$ family.

The Na-S cylindrical-shaped battery, in contrast, is a molten-salt battery with a sulfur cathode, sodium anode, and beta-alumina ceramic electrolyte [117]. Na-S batteries have very high theoretical energy densities (about five times that of a typical l-acid battery), and are inexpensive and non-toxic. However, the biggest challenge from the perspective of automobile applications is the operating range (270 to 350 °C), which also poses some serious safety issues. Despite such a prominent problem, an application of Na-S (prototype EV: 'Ecostar') was depicted by Ford in 1991 [65].

The recent and future trends are toward the development of Na-S batteries that can successfully operate at ambient temperature. However, ambient temperature operation presents the following bottlenecks: poor conductivity, low reaction rates, and 'shuttle' effect resulting in shorter lifespan [118]. A leading group of researchers at Ceramatec (2009) developed and investigated Na-S variants using NASICON membranes. The battery was demonstrated to effectively operate at 90 °C [119]. Similarly, in March 2011, Sumitomo Electric Industries and Kyoto University revealed a low-temperature molten Na-S battery operating under 100 °C, with double the energy density of Li-ion at a considerably lower cost [120]. In this context, the graphical layout of a typical Na-S battery is depicted in Figure 8b.

3.3.2. Metal-Ion Batteries

The metal-ion batteries are potential alternatives to Li-ion batteries, mainly including sodium-ion (Na-ion), zinc-ion (Zn-ion), and magnesium-ion (Mg-ion). Metal-ion batteries have some clear merits when compared with Li-ion batteries, such as material abundance, lower production costs, enhanced safety, and environmental friendliness [121].

According to several researchers, Na-ion batteries are expected to play an important role as the price of lithium keeps on increasing. The Na-ion battery is a rechargeable battery that uses sodium ions (Na^+) as its charge carriers. The working principle and design of the Na-ion battery are essentially similar to the Li-ion battery, except that Li is replaced by Na [121]. Subsequently, the electrolyte can either be aqueous or non-aqueous (molten or solid); however, an aqueous electrolyte results in poor electrochemical stability and limited energy density [38]. The non-aqueous electrolytes are, therefore, preferred, such as Na salt (sodium hexafluorophosphate) dissolved in an organic solvent. However, the energy density of Na-ion batteries is comparatively lower, therefore providing the same performance as of Li-ion but with a larger size/weight. A group of researchers [122] presented a Na-ion solid-state battery with a metallic Na anode and ceramic/polymer Na superionic conducting electrolyte. The prototype displayed competitive experimental performance. Given the relatively newer nature of Na-ion batteries, the performance indicators of Na-ion batteries can be improved by choosing innovative materials, such as carbonaceous materials for electrodes and intermetallic compounds for anode [121]. A prominent Chinese manufacturer, CATL, unveiled the first generation of commercial-scale Na-ion batteries, offering an energy density around 160 Wh/kg. Furthermore, these batteries can be charged up to 80% in about 15 min at room temperature [38]. The researchers at CATL are aiming for an energy density beyond 200 Wh/kg for the second generation of Na-ion batteries.

Zinc-ion-based aqueous batteries provide an acceptable energy density and have the intrinsic advantages of safety, environmental benefit, and being economical. However, some drawbacks are still unresolved and, therefore, under research, such as suitable cathode materials for the efficient intercalation of zinc ions [123]. Recently, a team proposed a reversible zinc-ion battery with a cathode made of MnO_2 [124]. Termed as a redox flow battery, the proposed type is considered a promising candidate for large-scale static energy storage. Another group of researchers modified the same technology to achieve a voltage of 1.95 V, which is the highest so far. Moreover, the proposed battery provided a gravimetric capacity of about 570 mAh/g and an energy density of around 409 Wh/kg. Another group of researchers developed an aqueous Zn-ion battery with a novel porous crystal cathode consisting of zinc pyrovanadate nanowires [125]. The resultant battery achieved a high specific energy of 214 Wh/kg, but lower lifespan.

3.3.3. Metal-Air Batteries

Being a newer technology, metal-air (M-air) batteries employ an anode made of pure metal and an external cathode made of ambient air, while the electrolyte is either aqueous or aprotic [126]. The energy capacity of the M-air battery is determined by the inherent capacity of the anode material. Nevertheless, in general, they can offer very high theoretical specific energy (easily comparable to and even exceeding to that of gasoline engines [11]), identifying the metal-air family as a prime (and potential) candidate for electrified automobiles [38]. The M-air family mainly includes zinc-air (Zn-air), aluminum-air (Al-air), iron-air (Fe-air), magnesium-air (Mg-Air), and calcium-air (Ca-air) beside the lithium-air

(Li-air) counterpart [127,128]. The ideal theoretical range can vary from ~11,700 Wh/kg (highest possible for Li-air) to ~1084 Wh/kg (lowest possible for Zn-air) [129,130]. With such elevated energy densities, the M-air batteries open up the possibility of an extensive travelling range with lowest possible weight. The M-air batteries can be manufactured into electrically/mechanically rechargeable variants, where, as of now, the mechanical variants are convenient for refueling and recycling. However, recharging is an aspect that is still not mature enough and, therefore, deserves more attention.

Within the M-air family, the Zn-air battery is the most promising one, but is still under extensive research [131]. This is because Zn-air batteries provide balanced attributes, higher theoretical energy density (~350 Wh/kg [132]), and relatively stable kinematics, leading to rechargeable variants. Moreover, Zn being an abundant and safe element can lead to cheaper, easy-to-handle, and recyclable batteries [133]. Several commercial auto manufacturers have already investigated Zn-air batteries, as evident from their utilization in Mercedes-Benz MB410 and GM-Opel Corsa Combo [20]. The composition of a typical Zn-air battery cell is presented in Figure 9a. The current key research areas related to Zn-air batteries are (i) enhancing the recharging efficiency; (ii) enhancing the kinematics at the anode and cathode; and (iii) expanding the lifespan for automotive applications. For example, a recent work has exhibited the usability of non-noble materials, considering an adequate catalytic performance during oxygen reduction (ORR) and evolution reactions (OER) [134]. As stated by the authors, both ORR and OER dictate the performance merits of metal-air batteries: open-circuit potential, cyclic lifespan, and energy density. The merits/demerits and performance of relatively abundant and cheap materials such as those that are carbon-based are comprehensively presented in the context of bifunctional oxygen catalytic activity.

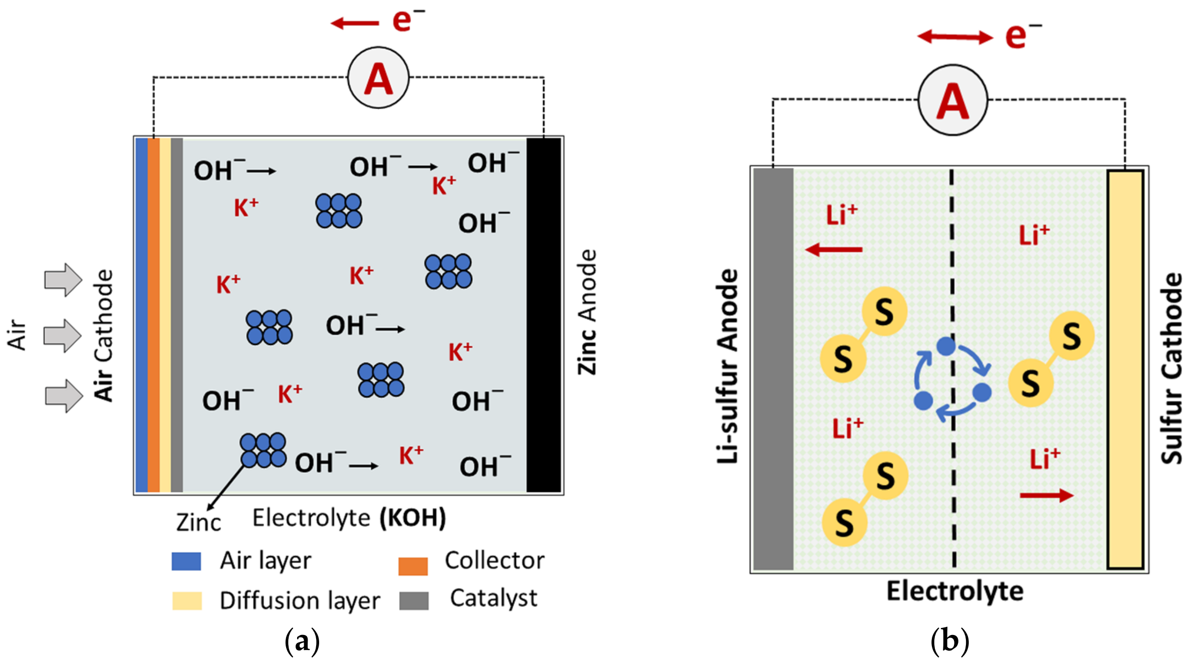


Figure 9. Composition of battery cell (future generation). (**a**) Zn-air cell. (**b**) Li-S cell.

The Li-air (Li-O_2) batteries can be classified into four categories according to the nature of the electrolyte: (i) nonaqueous; (ii) aqueous; (iii) hybrid aqueous/nonaqueous; and (iv) solid-state [20]. The Li-O_2 battery with a nonaqueous electrolyte can reach an extremely high theoretical energy density (~11,700 Wh/kg), thus making it competitive with gasoline termed a 'future power source' [20]. The aqueous Li-O_2 variant, in contrast, has a high risk of catching fire but shows a lower decomposition voltage. The hybrid technology combines the merits of both aqueous and nonaqueous types. Great efforts are, therefore, devoted to improving the operational efficiency and cycle life of hybrid Li-O_2 batteries, especially for the protection of electrodes. Nonetheless, many researchers recognize that lithium as a metal poses a challenging chemistry. Therefore, many years of fundamental research are required to successfully commercialize rechargeable Li-O_2 batteries. Additionally, poor electrical conductivity is another relevant problem associated with Li-air batteries [38].

3.3.4. Solid-State Batteries

From the Li-metal family, the solid-state batteries are among the key research themes and considered a viable future for high-performance electrified automobiles (future generation of batteries). The Li-based solid-state batteries are based on a Li metal anode and layered oxide cathode in combination with a solid electrolyte (solid polymers or inorganic solids) [135]. Among solid-state batteries, lithium-sulfur (Li-S) and lithium-air (Li-O_2) batteries are the most promising products from the perspective of automakers. Solid-state batteries in general can pose several problems, such as flammability and poor cycling performance.

Sulfur as an element has the features of high gravimetric capacity, low cost, and innate abundance. These features pushed researchers to exploit and investigate the chemistry of sulfur for battery applications. With a similar theoretical specific energy of more than 2500 Wh/kg, the Li-S battery with a solid electrolyte is considered a competitive candidate for next-generation energy storage devices. A group of researchers in [136] expect a bright future for the Li-S battery due to its higher energy density, better safety, broader temperature window, and lower manufacturing cost due to the abundance of sulfur in the Earth's crust. However, sulfur-based cathodes still suffer from poor electronic conductivity, which is a major bottleneck and hindering commercial acceptance [135]. Another technical obstacle is the passivation of the Li anode resulting in higher self-discharge rate and faster capacity degradation [137]. If these problems are well addressed, it is believed by researchers that Li-S solid-state batteries can be promising for high-performance automotive. A high-performance Li-S solid-state battery with a sulfide electrolyte and use of a thin silver-carbon layer, which contributes to a longer lifespan, is being studied by researchers [138]. Researchers have mentioned a technical issue about the charge-transfer process that may require solid-state batteries made up of ceramic/polymeric electrolytes. In this context, a typical Li-S battery cell is presented in Figure 9b.

Alongside the Li-S solid-state battery, the Li-air battery with a solid electrolyte is a potential candidate for next-generation electrified automotive. In 2015, a team at the University of Cambridge worked on Li-air batteries by developing a charging process capable of prolonging the battery life and efficiency [139]. The presented work resulted in a battery delivering high energy density with 90% efficiency and that could be recharged up to 2000 times. The solid-state Li-air batteries are, therefore, described as the ultimate batteries because they propose a high theoretical energy density of up to ten times the energy offered by regular lithium-ion batteries.

4. Battery Management and Modeling

Battery management and power control are the two most important decision-making units of onboard electronic control units (ECU). Usually, these units are interconnected and perform a series of critical operations for assuring reliable and safe operation from both the perspective of user experience and the vehicle itself. The power controller ensures optimal charging by external means (plugin option). This is achieved by manipulating the onboard charger (AC/DC and DC/DC with inherent isolation [20,140]) based on the information provided by the battery management unit (SoC, SoH, temperature, power limit, etc.) and external charger (if applicable). In addition to monitoring the battery charge, the power controller also monitors and regulates the operation of the electric motor while keeping the overall operation reliable and as safe as possible.

The battery management unit ensures the safe and reliable operation of battery pack. The real time data are first collected via embedded sensors and is then fed to battery modeling and state estimation algorithms (stored on the computer of the ECU). The crucial information about the state of the battery is, in turn, furnished, such as charge (SoC), health (SoH), temperature (SoT), power capability, etc. [20]. Based on the provided states, appropriate decisions are taken at the right time: temperature regulation of the battery pack based on ambient temperature and that of the battery; external charge control based on battery capability, the SoC, and information provided by the external charger; battery cell equalization and balancing; fault diagnosis and prognostic; safety warnings, protection measures, and bidirectional human–media interaction, etc. In this context, an abstract view of the battery management and power control unit is exhibited in Figure 10, though the illustrated unit may differ depending on the type of EV and corresponding automaker.

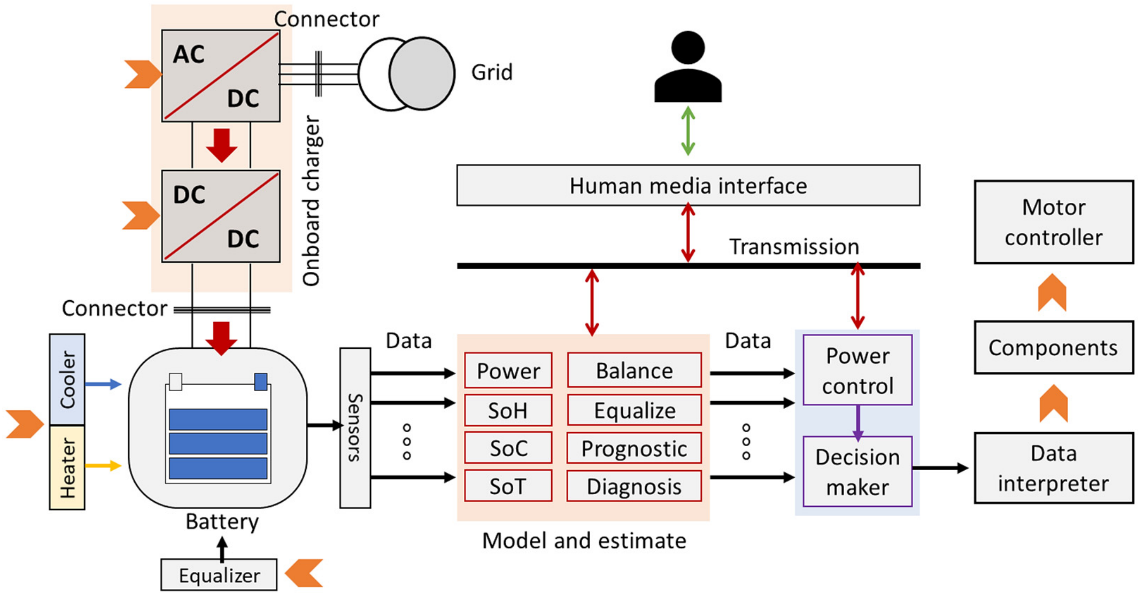


Figure 10. Conceptual illustration of battery management and power control unit.

Mathematically modeling the complex electrochemical behavior of a battery pack with an appropriate compromise between accuracy and complexity is an important prerequisite for onboard BMS. As battery models evaluate and provide critical information about battery packs, a well-developed scheme is mandatory. The provided critical information mainly comprises the estimation of battery states: SoC, SoH, power, temperature, etc. Given the provided information, the onboard management system performs a series of decisions to ensure reliable and safer vehicular operation. To mimic the electrochemical behavior of the battery pack and depending on the required operation, the modeling methods are broadly classified as follows: (i) electrical and/or equivalent circuits, (ii) electrochemical, (iii) empirical and semi-empirical, and (iv) data-driven [20,50–53,141].

4.1. Electrical (Equivalent Circuit) Models

Electrical equivalent models are widely exploited to model the complex behavior of battery packs and calculate the estimate of battery states [142,143]. This is because they use certain combinations of basic electrical passive elements: resistors (R) and capacitors (C).

The most fundamental electrical model (also known as the basic Rint model) is presented in Figure 11a [20,144]. As illustrated, the basic model is identified by a dependent open-circuit voltage source (V_{oc}) in series with resistance. The basic model is quite simple but does not consider the vital polarization effect. To solve this problem, the basic model can be extended to consider polarization, that is, by adding an RC tank unit in series [145]. The extended model is flexible in terms of improving the dynamic representation of the battery pack by adding a couple of RC tank units in series, as shown in Figure 11a. However, adding more RC tank units can increase the computational complexity and number of parameters to be identified and tuned [20]. Therefore, the equivalent configuration should be selected with an appropriate tradeoff between complexity, computational burden, and accuracy. Many researchers believe that the Rint model with two coupled RC tank units is sufficient to mimic the behavior of a battery pack.

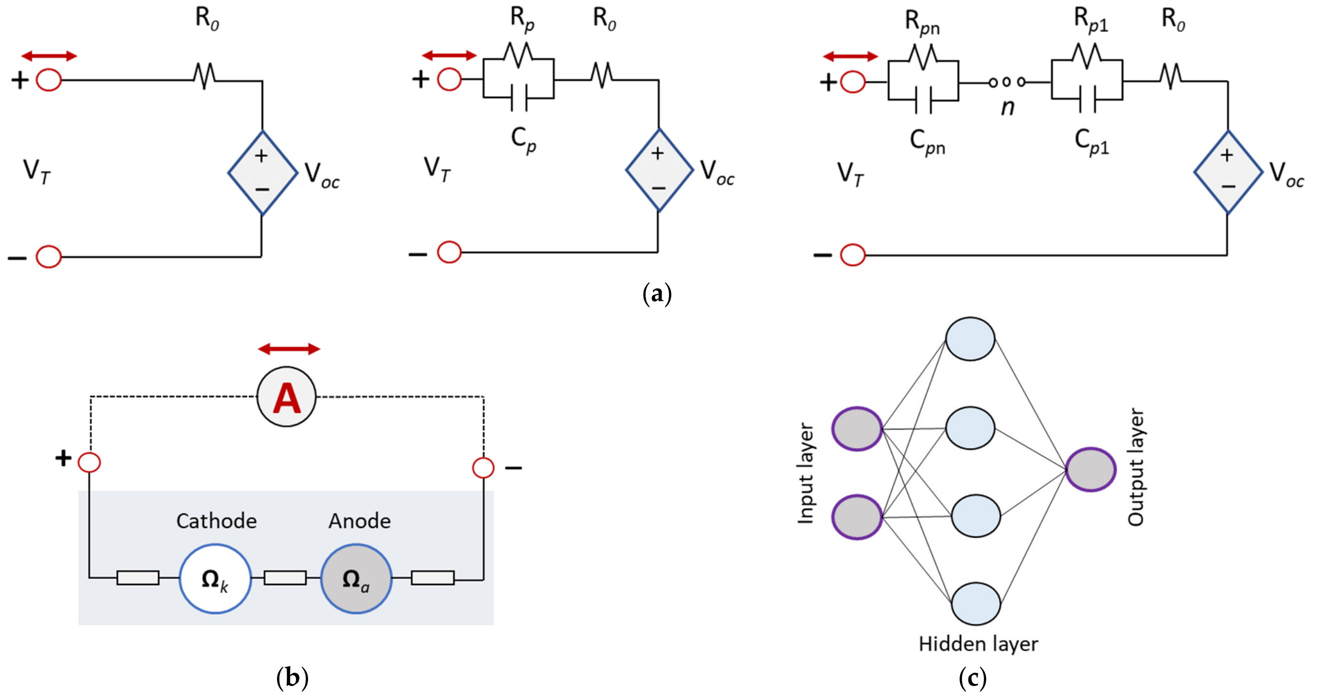


Figure 11. Graphical illustration of battery modeling techniques. (**a**) Electrical equivalent (basic, extended, and generalized). (**b**) Electrochemical. (**c**) Data-driven (neural network).

4.2. Electrochemical Models

Electrochemical models are essentially used to study, understand, and design batteries for EV applications. Such models mimic the complex battery behavior at the microscopic level based on multi-physics interpretation of nonlinear electrochemical reactions [20]. Currently, the electrochemical models are adequate, but at the cost of the following limitations: (i) several intercoupled nonlinear/linear equations, explaining the overall behavior of the battery, but requiring a global optimizer to solve these equations; (ii) a large number of parameters and boundary conditions, which must be tuned and initiated correctly, thereby affecting the performance of the model itself; and (iii) posing a significant computational burden and ill convergence problem due to previously discussed points [20,146,147].

The single-particle electrochemical model is considered the most mature and simplistic one; however, accuracy in its base form is on the lower side [20]. The abstractive layout of a single-particle model is presented in Figure 11b. The single-particle model is quite flexible in terms of modifications, as exhibited in [148], where electrolyte dynamics are incorporated to exhibit a good observance of the real parameters. Accordingly, to enhance the accuracy even further, a pseudo-two-dimensional model is proposed for simulating the complex electrochemical behavior of the studied battery pack.

Recently, reduced-order single-particle models have gained significant attention owing to their lower computational burden enabling real-time application, though the major associated drawback is the inaccuracy of predicted battery parameters. With this, a group of researchers in [149] have developed a reduced-order single-particle model considering the variable diffusivity of Li-ions, which enhances the accuracy of the predicted parameters. The authors have comprehensively illustrated the synthesis of the improved model and thereafter, the sensitivity analysis is performed concluding with experimental validation using a pouch type Li-cell at different load and temperature profiles. Another group of researchers in [150] have devised a reduced-order electrochemical model, which offers quite an accurate representation of complex battery behavior. However, the model is highly dependent on numerous parameters resulting in increased complexity. This also brings the problem of scalability, requiring several parameters to be tuned for application on a different battery pack. In this context, an effective parameter identification method is applied to a simplified yet accurate electrochemical model for Li-ion battery characterization [151]. The proposed electrochemical model is essentially thermally coupled, where solid-phase diffusion is considered to reflect the actual dynamics. The stepwise parameter identification process is established by extracting system dynamics from experimental data. The model is comprehensively validated with a galvanostatic discharge test with temperature range from -20 °C to 45 (°C).

4.3. Data-Driven Models

Data-driven approaches represent the newer generation of battery modeling techniques. They are among the key research trends, owing to the recent boom in AI and popularization of machine (and deep) learning methods such as neural networks, fuzzy inference systems, vector machines, etc. The data-driven models are black-box in nature; therefore, they are highly flexible and theoretically can be applied to any multi-physics nonlinear system to perform the intended task. However, this requires a thorough understanding of the system to be mimicked, and rigorous tuning of associated parameters, not to mention the huge computational burden particularly associated with deep learning models, for example, setting the layers (input, hidden, and output) of neural networks (Figure 11c) such that a well-trained network can provide an accurate estimate of the battery states.

The data-driven methods, especially machine (and deep) learning, have found recent applications for estimating battery states (health, temperature, etc.) [152]. Some of the applications of data-driven methods are as follows: vector machines [153], artificial neural networks [154], long-short-term memory networks, etc. A recent study exhibits the application of a data-driven approach to optimally configure the essential components of modern microgrids such as battery storage considering their degradation [155]. The efficacy of data-driven approaches is evident from satisfactory results in a diverse range of operating scenarios. The recent applications depict the general robustness of data-driven models compared to their conventional counterparts, though the requirement of training datasets and the associated computational burden are the major bottlenecks [156].

Among data-driven models, deep neural networks have witnessed recent attention. An application of a modified convolution neural network (CNN) is reported in [157], where techniques such as transfer learning and network pruning are exploited to address the shortcomings of conventional CNN, including training data dependency and computational burden. The accuracy of online capacity estimation is thereafter presented for four different LFP battery packs. Another innovative work is reported in [158], where the authors have extended the conventional CNN approach for estimating the complete charging curves just by collecting thirty points within ten minutes. Furthermore, the approach is generic in a way that it can be applied to any battery with a few training datasets by using a transfer learning process. It is worth mentioning here that the deep neural-networks can be consistently applied to a diverse range of batteries, such as SoC estimation of LFP battery [159] and co-estimation of LFP battery states in [160]. The data-driven methods can also be combined with other approaches such as pulse–current operation of Li-ion batteries in the context of stabilizing future grids [161].

Conclusively, data-driven models are promising for the application of battery modeling and state estimation, and their use is expected to rise with time as an ultimate solution [162].

5. Battery State Estimation

State estimation has a close affinity with battery modeling techniques (shown in Table 3), as it is regarded as the expected outcome of battery modeling. State estimators are among the most important components of BMS for EV applications, since accurate and timely estimation is essential for reliable and safer operation of battery packs. The estimated states mainly include charge (SoC), health (SoH), temperature (SoT), etc. Owing to its importance, the topic of battery state estimation is well reported and rigorously studied by several researchers. Battery state estimators are typically categorized as follows: (i) simplistic; (ii) filters; and (iii) data-driven.

Table 3. Battery modeling techniques with their suitable applications.

Technique	Complexity	Computation	Precision	Analysis	Maturity	Application for BMS
Electrical	L	L-M	M	H	H	Power and SoC
Electrochemical	H	M-H	M-H	M	M-H	Design and understanding
Data-driven	M	M-H	H	L	L	SoC, SoH, etc.

Legend: L (low), M (medium), H (high).

The simplistic estimators are easy to implement but are limited by moderate accuracy at best. The filter-based estimators provide precise estimation but are dependent on the understanding of the physical model itself. Finally, the data-driven models are model-independent, yet provide accurate estimation, but at the cost of computational burden and needing a significant amount of training data. The conclusive comparison of these estimators is provided in Table 4.

Table 4. Battery state estimators for electrified automobiles.

State Estimators		Qualitative Indicators				
Method	Mention	Implementation Level/Cost/App.	Data Required Training/Initial	Sensor Noise	Model Dependency	Precision
Simplistic	Lookup table Integrator Internal Ω and EIS	E/L/On	N/Y	S	N (Y *)	L-M
Filters	Kalman and particle	M-H/M-H/On	N/N	NS	Y	M-H
Data-driven	Neural network Vector machines Fuzzy inference	M-H/H/Of +	Y/N	NS	N	H

Legend: S (sensitive), NS (not sensitive), E (easy), L (low), On (online), N (no), Y (yes), M (moderate), H (hard), Of (offline). + Higher computational burden during the training phase. The application can be online but requires intensive training. * Resistance and EIS methods typically depend on system model such as equivalent electrical circuit.

5.1. Simplistic Estimators

Simplistic estimators are among the most-established methods with innate simplicity, ease of implementation, and greater technical maturity. However, most simplistic approaches, depending on their application, provide moderate accuracy at best. Their fundamental application is found in the form of a lookup table with the preserved relationship between open circuit voltage and SoC [20]. Typically, such a table is provided by the manufacturer, and is developed through rigorous field testing. A group of researchers reported the application of a lookup table in the context of BMS, where SoC is estimated based on the calculated open circuit voltage, and provided an offline table [163]. However, the shortcomings are obvious: (i) the lookup table is unique to a specific battery pack and is sometimes not provided by the manufacturer and (ii) the accuracy is profoundly affected by the presence of memory effect (nickel-based batteries), which can lead to unwanted estimation errors. Therefore, lookup table-driven methods are not suitable for high-precision applications.

The Coulomb counter (amp-hour integrator) is a popular and well-documented method for estimating the SoC of battery packs [60,164,165]. The Coulomb counter method is very easy to implement, as in theory, only a single current sensor and some simple calculations are required. Nevertheless, the initial SoC value (SoC_0) is usually required in order to use a Coulomb counter [60]. Therefore, Coulomb counting methods are supplemented with initial state estimators [58]. Another shortcoming is the accumulation of open-loop estimation errors, as well as poor estimation accuracy caused by natural capacity fade.

The internal resistance of the battery pack (calculated from the electrical circuit) can be mapped to provide crude information about SoH and capacity fade, etc. However, such methods have poor accuracy, as reported in [20]. The estimation accuracy can be improved by integrating additional techniques such as electrochemical impedance (EIS) for facilitating precise estimation of the battery states [58]. This means that simplistic estimators are usually assisted by other methods to improve the estimation accuracy.

5.2. Filter-Based Estimators

The filter-based estimators (Kalman and particle) are model-dependent. Therefore, they can provide superior accuracy and robustness against parameter drift, but generally at the cost of extensive computational complexity/burden. The Kalman filter (Kf) and its variants (adaptive, unscented, extended, etc.) are rigorously reported in the literature for battery state estimation: SoC, SoH, etc. [20,61]. A square root extended Kf is proposed in [166] to handle filtering variance in dynamic operating scenarios. Another application is depicted in [167], where cubature Kf is exploited to reduce design complexity while retaining scalability. With time, as the battery degrades, the performance of the baseline Kf method normally declines [20]. The adaptive and unscented Kf variants are effective estimators in such cases owing to less sensitivity against parameter uncertainty/variation and process noise.

Alongside the Kf-based methods, the particle filter (Pf) is a promising candidate for precise battery state estimation. The Pf-based estimators are suitable for highly complicated and nonlinear problems, such as capacity fade and SoH estimation [54]. A model-oriented Pf-based estimator is developed in [168] to predict the aging trajectories of Li-ion batteries, while gradient correction is added to reduce sensitivity to parameter variation. Another application is illustrated in [169], where a second-order Pf-based estimator is proposed for battery SoH estimation. Conclusively, the filter-based estimators (Kf and Pf) are geared toward accuracy/precision but require detailed understanding of models and appropriate adaptations to work against parameter variations and uncertainties.

In a nutshell, although they are proficient and reliable, the model-based estimators depend on complex differential and nonlinear equations, posing computational challenges, as well as tuning them and finding several unknown parameters. Moreover, they are not generic, and an estimator operating for a specific battery may not work the same way for other batteries. This shortcoming has led to significant attention being paid to model-independent and data-driven approaches.

5.3. Data-Driven Estimators

Data-driven methods are considered a viable future owing to the following advantages: black-box nature (model-independent), resistance to parameter variation, and scalability. However, these advantages come with a higher computational burden and need for a significant amount of training data with appropriate quality (for example labelling) in the context of estimation accuracy. Data-driven methods have found several recent applications for battery state estimation, such as neural networks, vector machines, fuzzy inference, metaheuristic [152,153,170,171], etc. Among the major shortcomings is that an inconsistent dataset can lead to an unavoidable estimation inaccuracy. For this, a fractional-order physics-informed recurrent neural network is proposed in [172] for battery state estimation, where the performance is enhanced by incorporating fractional-order gradient functions during the backpropagation step.

Mostly, the applications are estimating SoH and capacity fade, and predicting the remaining useful life of battery packs. A group of researchers in [63] reviewed the data-driven machine learning approaches for predicting battery states. To enhance the accuracy of battery health estimation, least-square vector machine and model-based Pf are hybridized as an effective joint supervision approach [173]. Similarly, an application of a global meta-heuristic optimizer (non-dominating sorting genetic algorithm) is illustrated in [174] for data-driven SoH estimation.

Deep learning neural networks are also very promising for battery state estimation. For example, a convolutional neural network-based estimator is proposed in [157] to provide fast yet accurate battery capacity forecasting by employing a small dataset. Another application of convolutional neural networks is exhibited in [175] for the accurate estimation of the heat generation rate and voltage distribution of Li-ion batteries in the context of EVs. As indicated in [176], heat generation rate estimation is a very important factor for accurate and timely decision-making within the framework of effective BMS of high-performance EVs, where a novel physics-informed neural network is employed and validated in a diverse range of driving conditions. The performance and scalability of deep models is, however, dependent on the diversity and quality of the training dataset, which is the major shortcoming beside the computational burden associated with the training phase. Distinctly, the data-driven models can be integrated with classical electrochemical perceptions; some examples are presented in the recent literature where data-driven electrothermal models are proposed with the aim of estimating battery degradation, modeling SoH, and predicting the effect of temperature on battery performance.

6. Open Discussion: Challenges, Opportunities, and Key Developments

Batteries and associated technologies are among the key elements and main factors that shape the future potential of electrified vehicles. It is, therefore, essential to understand the perspective of automakers and consumers with equal importance. While the common user thinks mostly about fundamental attributes such as range, cost, and driving experience (power, charging time, etc.), automakers have a more detailed understanding and naturally more challenges to deal with. In this context, finding the perfect battery chemistry is quite challenging, as it involves assessing several elements: safety, performance, cost, range, thermal performance, and reliability across the entire battery lifecycle. Moreover, several aspects of design, economics, and politics are coupled with battery design for electrified automobiles.

To identify potential opportunities and to pinpoint key future trends, understanding the complete battery cycle is the most critical step. In general, from the perspective of automakers and battery designers, the most abundant and safe-to-use materials/minerals are, indeed, on the wish list, as they are easier to extract, recycle, process, etc. This can ultimately assist in controlling the cost factor of the future generation of batteries. However, it is not common that such abundant mineral can meet the needs of a common user; for example, the driving experience (power delivery and extended range) may not be competitive with that of the current Li-ion generation with exotic mineral. Therefore, a complex engineering process is required to find a suitable compromise between several conflicting factors, such as manufacturing price, driving performance, safety, recycling, etc., in order to reach an appropriate choice.

In this context, the introduced distinct qualitative factors (design markers and performance indicators) can play a pivotal role in reaching the required appropriate choice. The battery performance indicators mainly include specific power/energy (higher power delivery, less weight, and autonomy), cyclic lifespan (longer life), etc., while the key design markers include manufacturing cost, minerals (abundance, toxicity, and maturity), etc. A suitable synergy between the qualitative factors can help to identify the suitable generation of batteries for electrified vehicles, with the potential to provide reasonable driving performance but with a lower manufacturing price and higher safety.

Through the introduced qualitative factors, a particular battery can also be associated with an appropriate automotive application. For example, the LTO battery provides very higher power density and cyclic lifespan, which makes it suitable for the start–stop functionality of eco-vehicles as well as application in gasoline and fuel cell hybrids, where a smaller battery with fast response is generally required, though the higher baseline price of LTO batteries is the major bottleneck for large-scale applications. Similarly, the LFP battery has a class-leading cyclic lifespan with highest safety (among the Li-generation) and an adequate price bracket, which places LFP batteries among the best choices for EVs where an extended travelling range is not required (small EVs, and given the fact that the energy density of LFP batteries is inferior to LCO and NMC batteries). Likewise, for exotic electric vehicles where exceptional performance and an extended travelling range is required, the cutting-edge Li-ion batteries such as NMC are among the best choices for automobile manufacturers. From the future generation of batteries, the Zn-air technology has the potential to supersede existing Li-based technology in terms of energy density, safety, and material abundance. However, its commercial success totally depends on if the shortcomings of Zn-air technology such as proper rechargeability and efficiency are addressed. In a nutshell, the introduced qualitative factors can provide the complete picture for reaching a rational application-oriented choice. Accordingly, a comparison between state-of-the-art battery technologies for EVs is presented in Figure 12. Two radar charts with all-round assessments are provided (key performance indicators and design markers).

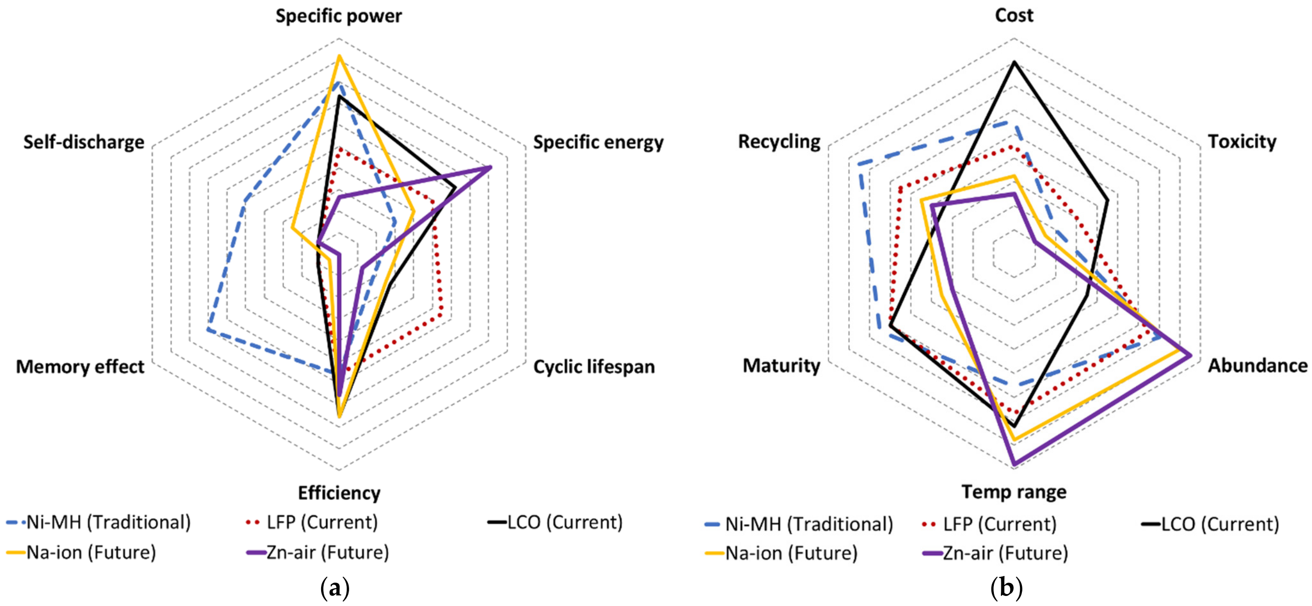


Figure 12. Generation-wise comparison among batteries for EV applications. (**a**) Key performance indicators. (**b**) Key design markers.

It can be observed from Figure 12 that the traditional generation of batteries (Ni-MH, used in the earlier generation of Toyota hybrid vehicles) has limited energy density and lower efficiency. Therefore, with time, auto manufacturers have replaced the traditional batteries with high-performance Li-based batteries. The current generation of high-performance batteries (LFP, NMC, LCO, etc.) are mostly lithium-based owing to their distinct merits such as higher specific energy and power density (higher autonomy, lesser weight, superior power delivery, etc.). However, the problem of Li-based batteries is related to minerals, cost, toxicity, etc. (lithium and cobalt are the essential elements of several Li-based batteries, and are toxic, difficult to access, and costly). It is expected that the access to strategic minerals for high-performance Li-ion batteries will become difficult with time, which would surely impede the progression of the Li-based current generation of batteries, therefore increasing their price with time. With this fact, the search for the next generation of batteries is underway, such as zinc-air and Na-ion batteries with adequate performance indicators but lower manufacturing price, less toxicity, and abundant minerals. However, for now, such batteries have lower maturity and several implementation problems. The results and discussion clearly show that that Li-based batteries would dominate the EV battery market, both currently and in the near future. However, some cutting-edge technologies such as solid-state, metal-air, sulfur-based, and metal-ion batteries are likely to be the next-generation EV batteries with an adequate trade-off between performance indicators and design markers. Another important aspect is the application of Li-ion batteries for ancillary and vehicle-to-grid services, as depicted in [177].

Battery modeling and estimation methods are an important aspect in the context of battery management systems, ensuring that the driving experience is reliable and safer. Currently, most high-performance and commercial batteries are Li-based, so cutting-edge research is focused more on modeling and estimation methods for Li batteries. With this, there is a significant gap, and potential avenues exist to develop state-of-the-art techniques applicable to the future generation of batteries, including metal-ion, metal-air, and solid-state batteries. In general, the data-driven methods can play a vital role due to their black-box nature and the fact that less effort is required to a tune data-driven technique for another battery when it is already performing well for a particular battery.

7. Conclusions and Perspectives

The role of batteries and associated technologies in the ongoing success and future direction of electrified automobiles is evident. Given the importance of this topic, it is pivotal to review these technologies and determine future directions, which can help academia, industry, and automakers. With this motivation, this article critically examines state-of-the-art battery technologies from the perspective of automobile manufacturers, provides insightful discussions, and facilitates key technological trends.

It is compulsory to understand the complete battery cycle from the perspective of automakers. In this context, the complete battery cycle is first described. Several interconnected aspects including manufacturing, application, and recycling are detailed. Based on this, two distinct qualitative factors are introduced: key performance indicators and design markers. Thereafter, the generations of batteries for EV applications (traditional, current, and futuristic) are reviewed and analyzed via the introduced qualitative factors, which effectively leads to major development trends and probable evolutions for battery technologies. Recent battery modeling and state estimation methods are also comprehensively discussed in relation to battery management and power control units. Accordingly, the promising modeling methods are identified and ranked based on key next-generation requirements: accuracy, computational load, scalability, resilience, implementation, maturity, etc. This article is concluded by presenting a techno-economic assessment of what to expect, as well as highlighting future challenges and opportunities. The intercomparison of state-of-the-art battery technologies for EVs is presented via radar charts with all-round assessments.

The key findings show that precious and strategic minerals such as lithium and cobalt (extensively used in the current generation of Li-based batteries) are becoming very expensive due to unprecedented demand and political/demographical problems, posing a great challenge for battery manufacturers. This challenge is motivating researchers and institutes to limit the usage of strategic minerals. Subsequently, extensive research on the development of alternate technologies and the future generation of high-performance batteries is underway. In this context, the aim of the future generation of batteries is to exploit minerals with innate abundancy, least toxicity, and enhanced safety (such as sodium, sulfur, zinc, manganese, iron, aluminum, etc.), then to assemble them in innovative ways for achieving high-performance electrochemical storage systems. It is, therefore, expected that several technological breakthroughs may emerge soon in the context of the future generation of batteries.

Among battery modeling and estimation methods for the future generation of electrified vehicles, the data-driven and hybrid approaches are expected to lead owing to several advantages: their black-box nature and effective scalability, higher accuracy, and timely decision-making. However, several shortcomings should be properly addressed so that these methods can completely replace the conventional ones. The fundamental key will be to find an appropriate compromise between accuracy, computation, and implementation.

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Abbreviations

BEV	Battery electric vehicle
BSS	Battery storage system
BMS	Battery management system
DQFs	Distinct qualitative factors
ECU	Electronic control unit
EIS	Electrochemical Z spectroscopy
EVs	Electric vehicles
FCHEV	Fuel cell hybrid electric vehicle
GHG	Greenhouse gasses
GHEV	Gasoline hybrid electric vehicle
HEVs	Hybrid electric vehicles
KPIs	Key performance indicators
KDIs	Key design indicators
Kf	Kalman filter
Pf	Particle filter
r-HEV	Range extender hybrid vehicle
SoC	State-of-charge
SoH	State-of-health
SoT	State-of-temperature
VRLA	Valve-regulated lead-acid

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