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Review article

Overview of batteries and battery management for electric vehicles

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ABSTRACT

Popularization of electric vehicles (EVs) is an effective solution to promote carbon neutrality, thus combating the climate crisis. Advances in EV batteries and battery management interrelate with government policies and user experiences closely. This article reviews the evolutions and challenges of (i) state-of-the-art battery technologies and (ii) state-of-the-art battery management technologies for hybrid and pure EVs. The key is to reveal the major features, pros and cons, new technological breakthroughs, future challenges, and opportunities for advancing electric mobility. This critical review envisions the development trends of battery chemistry technologies, technologies regarding batteries, and technologies replacing batteries. Wherein, lithium-ion batteries, lithium-metal batteries (such as solid state batteries), and technologies beyond lithium ('post-lithium') will be actively explored in the next decades. Meanwhile, the data-driven electrothermal model is promising and identified with an impressive performance. Technologies of move-and-charge and wireless power drive will help alleviate the overdependence of batteries. Finally, future high-energy batteries and their management technologies will actively embrace the information and energy internet for data and energy sharing.

Contents

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Nomenclature

EV	Electric vehicle
HEV	Hybrid electric vehicle
PHEV	Plug-in hybrid vehicle
FCEV	Fuel cell electric vehicle
BEV	Battery electric vehicle
ICE	Internal combustion engine
KPI	Key performance indicator
WPT	Wireless power transfer
WDT	Wireless drive transfer
V2V	Vehicle-to-vehicle
V2H	Vehicle-to-home
V2G	Vehicle-to-grid
IoT	Internet of Things
LIB	Lithium-ion battery
LMB	Lithium-metal battery
SSB	Solid state battery
LSB	Lithium–sulfur battery
LCO	Lithium cobalt oxide
LFP	Lithium iron phosphate
LMO	Lithium manganese oxide
NCM	Lithium nickel cobalt manganese oxide
NCA	Lithium nickel cobalt aluminum oxide
LNO	Lithium nickel oxide
LTO	Lithium titanium oxide
VRLA	Valve-regulated lead–acid
SIB	Sodium-ion battery
ZIB	Zinc-ion battery
MIB	Magnesium-ion battery
DIB	Dual ion battery
DCB	Dual carbon battery
BMS	Battery management system
BTMS	Battery thermal management system
SOC	State of charge
RUL	Remaining useful life
SOH	State of health
SOT	State of temperature
SOF	State of function
SOB	State of balance
SOP	State of power
USA	United States of America
EU	European Union
RoW	Rest of world
AC	Alternating current
DC	Direct current
HF	High frequency
PFC	Power factor correction
EIS	Electrochemical impedance spectroscopy
ECM	Equivalent circuit model
IOM	Integral-order model
FOM	Fractional-order model
RC	Resistor–capacitor
OCV	Open-circuit voltage
KF	Kalman filter
PF	Particle filter
PCM	Phase change material
ML	Machine learning
NN	Neural network
CC	Cloud computing
AI	Artificial intelligence
VIEI	Vehicular information and energy internet

1. Introduction

Coal-fired power plants with inappropriate after-treatment have deteriorated our environment and seriously declined global air quality. Industrial gas emissions and internal combustion engine (ICE) vehicles have further exacerbated urban air pollution. With ever-increasing environmental deterioration, various electric vehicles (EVs) are being strategically developed in a global context (Chau and Chan, 2007). Wherein, these automobiles can be classified into four types: (i) hybrid electric vehicles (HEVs), (ii) plug-in hybrid electric vehicles (PHEVs), (iii) fuel cell electric vehicles (FCEVs), and (iv) fully battery electric vehicles (BEVs) (Chan, 2007; Sanguesa et al., 2021; İnci et al., 2021; Liu et al., 2021f). The popularization of EVs has many advantages, including (i) suppressing the oil dependence and gas emissions, (ii) reducing the carbon footprint, and promoting carbon neutrality, (iii) sparking a green transport revolution, and promisingly combating climate change (Chau, 2016). Highly dependent on the source of electricity, the development of EVs toward globalization is recognized as one of the most effective solutions.

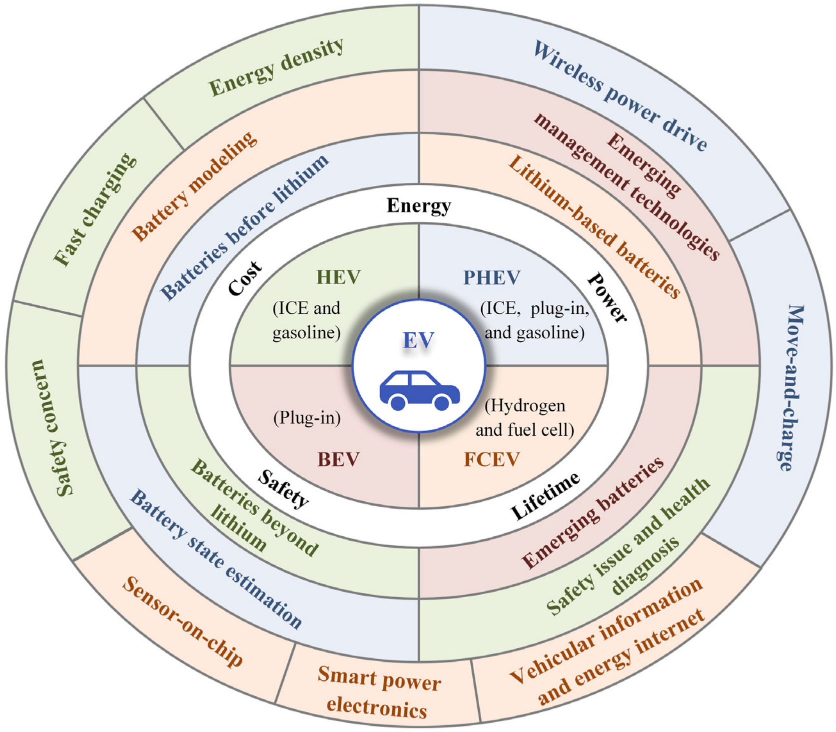

Fig. 1. Research hints of this review work.

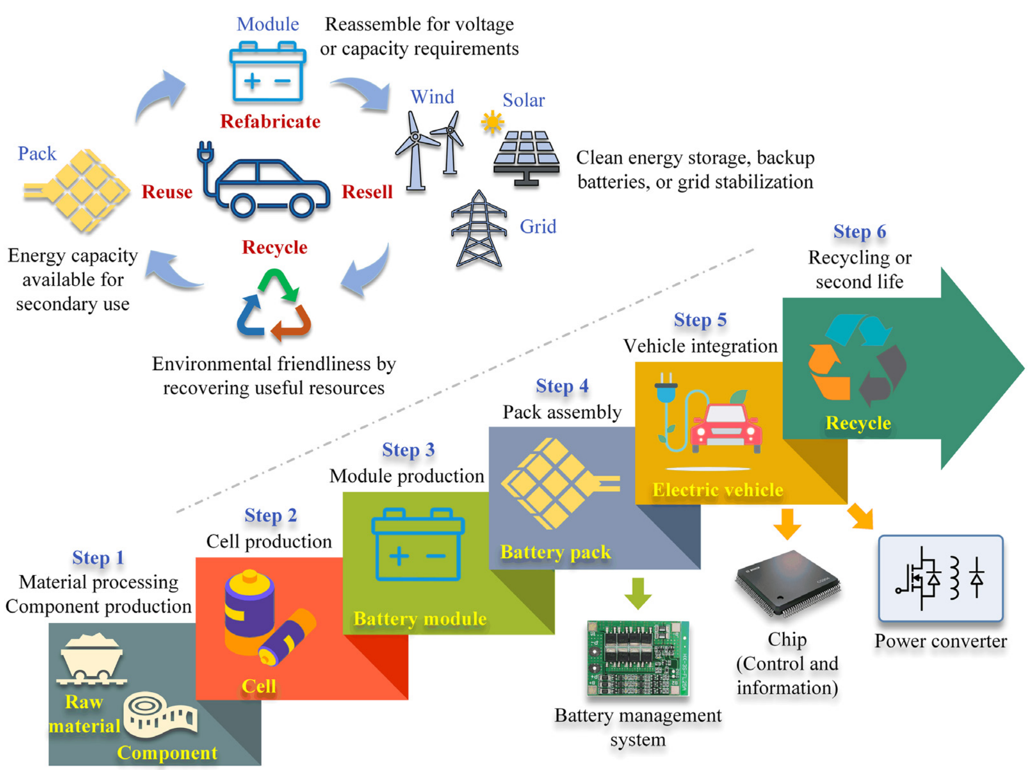

Fig. 2. Industrial value chain and circulation of rechargeable batteries for electric vehicle mobility.

Besides the machine and drive (Liu et al., 2021c) as well as the auxiliary electronics, the rechargeable battery pack is another most critical component for electric propulsions and await to seek technological breakthroughs continuously (Shen et al., 2014). Fig. 1 shows the main hints presented in this review. Considering billions of portable electronics and millions of EVs, advances in the battery's key performance indicators (KPIs), including (i) energy, (ii) power, (iii) lifetime, (iv) safety, and (v) cost, are especially attractive for industries and consumers (Wang et al., 2016a). These central KPIs can be further subdivided into (i) specific energy (Wh kg^{-1}) and energy density (Wh L^{-1}), (ii) specific power (W kg^{-1}), power density (W L^{-1}), and specifically charge acceptance (= fast charging), (iii) cycle and calendar life, (iv) mechanical, electrical and thermal safety and (v) cost per energy content. Fig. 2 demonstrates the industrial value chain of rechargeable batteries for EV mobility, which involves 6 steps in total: (i) material processing and component production, (ii) cell production, (iii) module production, (iv) pack assembly, (v) vehicle integration, and (vi) recycling or second life. The second life batteries can experience four processes of (i) recycle, (ii) reuse, (iii) refabricate, and (iv) resell to effectively improve their sustainability (Ueda et al., 2010).

Currently, among all batteries, lithium-ion batteries (LIBs) do not only dominate the battery market of portable electronics but also have a widespread application in the booming market of automotive and stationary energy storage (Duffner et al., 2021; Lukic et al., 2008; Whittingham, 2012). The reason is that battery technologies before lithium (e.g., lead–acid or nickel-based batteries) and battery technologies beyond lithium, so-called 'post-lithium' technologies, such as sodium-ion batteries (SIBs), mainly suffer from significantly lower energy density and specific energy compared to state-of-the-art LIBs. Lithium-metal batteries (LMBs), especially solid state batteries (SSBs), are the most promising and emerging technology to further remarkably increase the energy density and driving range of EVs, however, this technology needs further research and development to meet lifetime, fast-charging and cost requirements. Accordingly, Fig. 3 indicates that the global battery industry is growing rapidly and will exceed 2500 GWh in the next decade (Alliance, 2019). Fig. 3(b) and (c) show the trends of battery demands concerning different applications and regions, respectively, where the electric mobility brings an increasing demand to the modern battery industry. China will gradually decrease the percentage of battery industry, while the rest of world (RoW) will gradually increase its percentage. Government policies have advocated developing electric vehicles and new energy automobiles, which will further stimulate the booming development of battery materials and vehicular computer science towards smart mobility. With the global theme of carbon neutrality, China announced that the emission peak will be reached before 2030. By 2030, 50% of new vehicles will realize zero emission in the USA. By 2035, almost all vehicles should achieve zero emission in Europe. To be comparable to fossil fuel vehicles, the energy density of LIBs is expected to reach a goal of ~500 Wh kg^{-1} for EV applications (Chen et al., 2019a), which is quite a great challenge for current battery chemistry (Dunn et al., 2011; Goodenough and Park, 2013; Tarascon and Armand, 2011). Many researchers and institutes believed that LMBs, in particular, such as SSBs, are one of the most promising candidates for high-power electric propulsions. Further technological breakthroughs may emerge in searching for more reliable and safer anode materials (Placke et al., 2017). In the technologies beyond lithium, SIBs exhibit some comparable KPIs to LIBs.

On top of batteries, battery management is crucial to ensure the reliable and safe operation of EV batteries. During the charge/discharge cycling, it facilitates the batteries to exert their optimal performance and prolong their service lives. Thus, a battery management system (BMS) (Xiong et al., 2018b; Hannan et al., 2018) is involved in each EV and performs a series of functions, including (i) battery state estimation, (ii) battery cell balancing (Ouyang et al., 2019) and pack charging/discharging control (How et al., 2020), (iii) thermal management (Zhang et al., 2018b; Yu and Chau, 2009), (iv) fault prognosis (Li et al., 2021g) and health diagnosis (Song et al., 2021), and (v) correspondence. The power management strategy of drive trains deserves to be emphasized for optimizing energy utilization (Chau and Wong, 2002). In addition, battery modeling (especially data-driven models) is to provide a virtual representation to imitate the battery electrochemical behaviors (Xie et al., 2020a). In aspects of hardware, the sensors can sense and return various battery parameters for model building and state estimating. The chips (or controllers) will process the battery information and issue control instructions, and thus they govern the power converters to realize the power conversion and information interaction. In aspects of software, with continuous upgradations of information communication and computer, the BMS may actively embrace some emerging technologies (Ng et al., 2020), such as artificial intelligence (AI), cloud computing (CC), and blockchain technology.

In recent years, wireless power transfer (WPT) technologies (Liu et al., 2018; Choi et al., 2015) may help deploy the roadway charging lanes to reduce the over-dependence of batteries for EVs. This move-and-charge scheme improves the flexibility and convenience of online EV charging (Jiang et al., 2018). Nevertheless, battery swapping (Infante et al., 2020) is still a swift and efficient way of energy refueling, thus being widely accepted by shuttle buses. Besides, the vehicle-to-vehicle (V2V), vehicle-to-home (V2H), vehicle-to-grid (V2G) operations (Liu et al., 2013) challenge the battery cycle life (Zhang et al., 2019b) due to the need for frequent charging or discharging. In the future, new sensor-on-chip, smart power electronics, and vehicular information and energy internet (VIEI) will greatly advance the modern BMS which will promote vehicular data and energy sharing.

The main purpose of this article is to review (i) the state-of-the-art and emerging batteries, and (ii) the state-of-the-art battery management technologies for EVs comprehensively. Wherein, various battery technologies and battery management technologies are both elaborated. Focusing on the above two objectives, major features, pros and cons, new technological routes, possible breakthrough directions, future challenges and opportunities are delineated to propose a development blueprint for EV applications. Finally, battery chemistry technologies, technologies regarding batteries, and technologies replacing batteries will work together to meet the future energy demand and electric mobility.

2. Electrochemical energy storage technologies

The electrochemical energy storage sources are classified in detail as shown in Fig. 4, where the mainstream is the power batteries rather than fuel cells for current EV applications. Occasionally, EVs can be equipped with a hybrid energy storage system of battery and ultra- or supercapacitor (Shen et al., 2014; Burke, 2007) which can offer the high energy density for longer driving ranges and the high specific power for instant energy exchange during automotive launch and brake, respectively. The fuel cells can offer zero emissions with satisfactory power and energy densities, but their development is relatively slow (Shen et al., 2014). Among various batteries, the protagonists are the lead–acid batteries, nickel-based batteries, and in particular LIBs (Hannan et al., 2018) at different stages of EV development. Over the development history of batteries, LIBs can be regarded as a significant advance in battery technology due to their superior KPIs especially in terms of high energy, long cycle life, and high safety (Schmuch et al., 2018; Gong et al., 2015; Winter et al., 2018). Besides, high-temperature batteries typically operate at 270~400 °C and are of high potential with the advantages of higher specific power and specific energy. The metal/air batteries are differentiated by their metal types as the anode, such as lithium metal or zinc metal. And they enjoy higher specific energy but suffer from insufficient cycle life. In addition, the

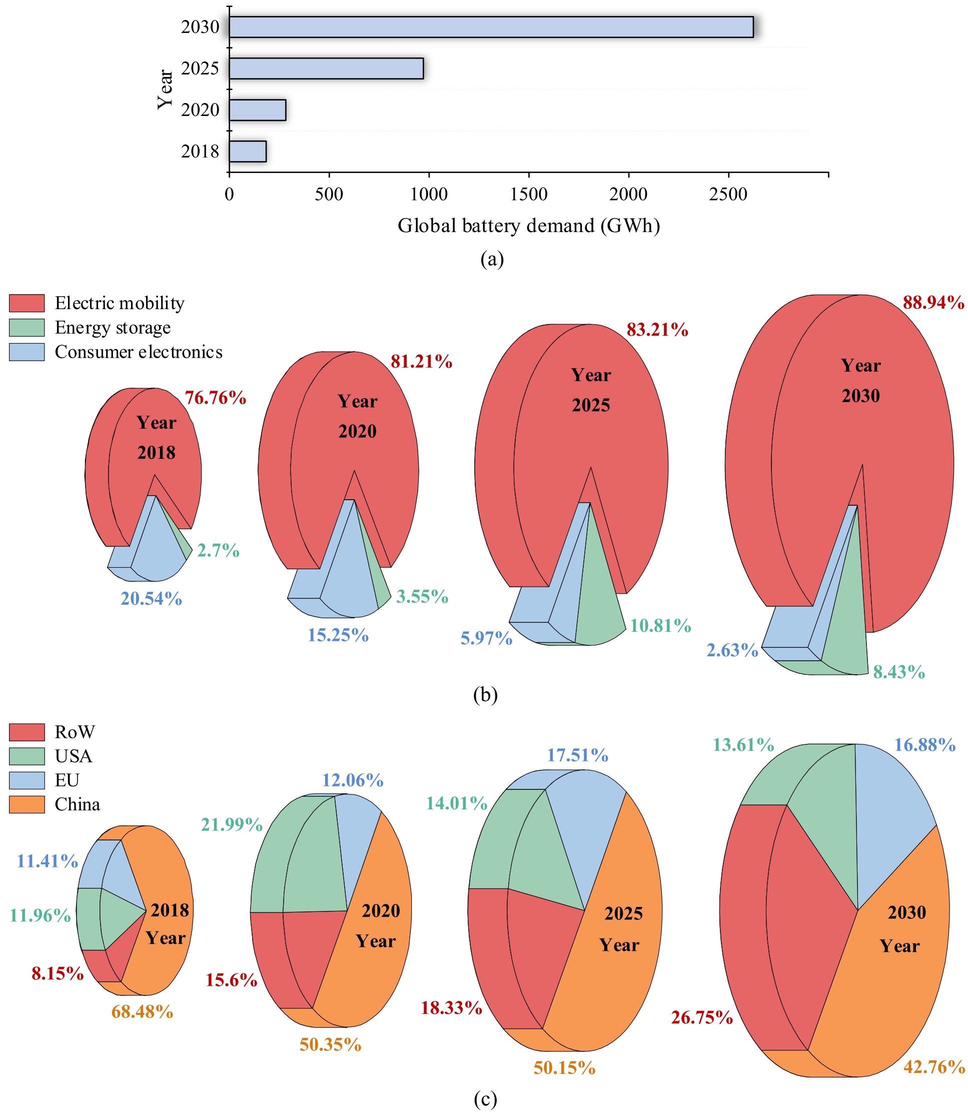

Fig. 3. Global battery industry. (a) Growth. (b) Demands by applications. (c) Demands by regions.

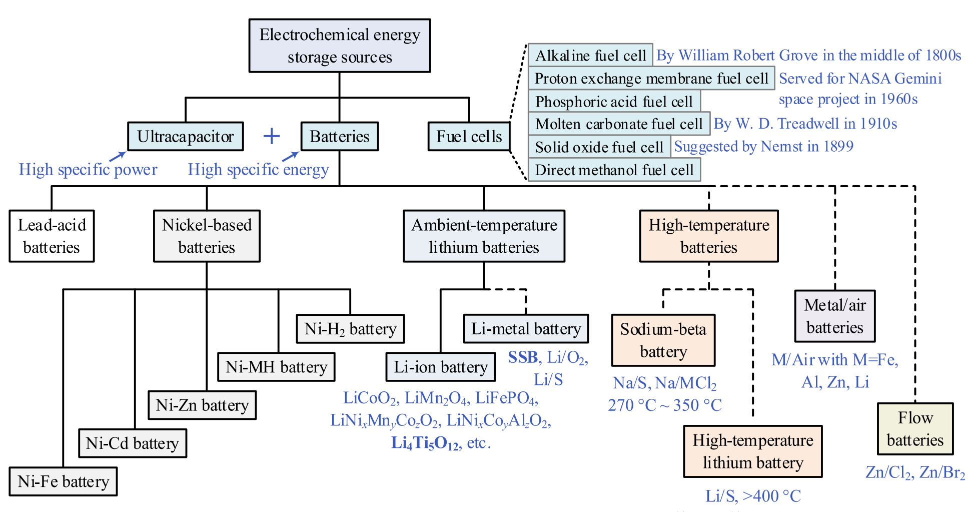

Fig. 4. Classification of electrochemical energy storage sources.

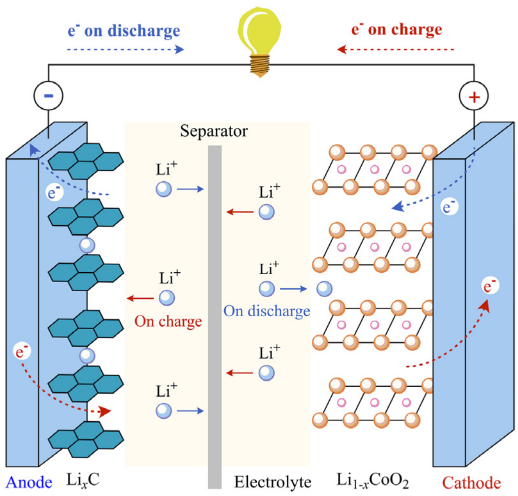

Fig. 5. Schematic of an exemplified lithium-ion battery cell (Goodenough, 2018).

flow batteries are more like fuel cells rather than conventional batteries. Other metal-ion candidates, such as zinc-ion (Konarov et al., 2018), magnesium-ion, and aluminum-ion batteries, require further research and development to identify their suitability for EV applications. As an exception, SIBs are much further developed than other metal ion technologies (Mg, Zn, Al, ...). Their market entrance for possible applications will most likely be much sooner (CATL, 2021). In the past, lead–acid batteries are only used as "starter batteries" and are not intended to power cars for long driving ranges. In recent years, LIBs have gradually replaced the lead–acid and nickel-based batteries and will dominate the EV market for powering our transportations in the next decade(s).

3. State-of-the-art batteries

3.1. Fundamentals

For EV propulsions, LIBs have been widely used after the successful commercialization, thanks to their intrinsic superiority in energy, safety, and lifetime. A LIB cell comprises three major parts—anode, cathode, and electrolyte (including separator), and the electrochemical innovations are mainly focused on these three parts for the increasing improvements on battery KPIs. As an illustration, Fig. 5 shows the schematic of an exemplified LIB cell, in which the lithium ions shuttle between two electrodes during the charging and discharging processes (Goodenough, 2018). Except for the internal LIB cell, the external circuit conducts the electrons for power sourcing and sinking. Importantly, both the high energy density and the specific energy can be guaranteed via material and battery design (Zhang et al., 2018b).

3.2. Advanced batteries

The lithium-ion batteries were gradually commercialized from 1991, while two types of primary batteries—zinc–manganese dioxide ($Zn–MnO_2$) battery and lithium-metal systems were designed in the 1866 and late 1960s, respectively. Both primary batteries came earlier than the LIBs. Fig. 6 (top) shows the milestones of primary and secondary (rechargeable) battery evolutions.

3.2.1. Battery technologies before lithium

Before the popularization of lithium batteries, two candidates of lead–acid battery and nickel-based battery were invented in 1859 and 1899, respectively. Until now, the lead–acid rechargeable battery remains to be used in some specific scenarios including the vehicles for starting, lighting, and ignition. However, its specific energy and energy density are both relatively low (up to ≈40 Wh kg^{-1} and 90 Wh L^{-1}) as compared with the state-of-the-art LIBs (≈260 Wh kg^{-1} and 700 Wh L^{-1} at cell level) (Schmuch et al., 2018). Next, the battery industry entered a new era of nickel, typically such as the nickel–zinc (Ni–Zn) battery and nickel metal hydride (Ni–MH) battery. The Ni–Zn battery possesses the advantages of high specific energy and low material cost, but its drawback of short cycle life limits the commercialization. Differing from the Ni–Zn battery, the Ni–MH was also equipped in BEVs and HEVs with specific energy and energy density of up to 80 Wh kg^{-1} and 250 Wh L^{-1}, respectively.

(1) Lead–Acid Batteries

As the first commercial battery, the lead–acid battery has dominated the market for more than a century, thanks to the advantages of mature technology and low cost (Garche et al., 2017). Typically, the valve-regulated lead–acid (VRLA) battery (Rand, 2009) has attained important advancements in terms of specific energy, specified power, and recharging speed, which is more suitable for vehicle applications. Moreover, it possesses some key merits of good performances in both low and high temperatures, high energy efficiency, and flexible size selection. Bipolar VRLA battery and UltraBattery™ can be regarded as the most promising lead–acid candidates (Wong and Chan, 2012).

(2) Nickel-Based Batteries

Using the nickel oxyhydroxide as the cathode material, various types of batteries were developed, including nickel–iron (Ni–Fe), nickel–cadmium (Ni–Co), nickel–zinc (Ni–Zn), nickel metal hydride (Ni–MH), and nickel–hydrogen ($Ni–H_2$). Typically, the Ni–Zn battery has the highest cell voltage of 1.6 V nominally in the nickel-based family. Superior to the Ni–Co battery, it achieves higher specific energy and more environmental friendliness because of non-toxicity. Also, it has a good tolerance of over-charge and over-discharge, high-rate performances for charge and discharge, and wide operating temperature. Nevertheless, because of the partial solubility of zinc species in the electrolyte, the Ni–Zn battery mainly suffers from a short cycle life of around 300 cycles only which severely limits its commercialization. Until now, it is still a research topic in battery chemistry (Zeng et al., 2017; Chen et al., 2019b). Besides, the Ni–MH battery has been well embraced by EV markets since 1992, which should be owing to its proven technology and good KPIs. Its nominal cell voltage is 1.32 V, and the specific energy is relatively higher than the lead–acid battery. The hydrogen absorbed in the metal hydride is used as the anode material (Hariprakash and Shukla, 2009). Numerous battery manufacturers have actively engaged in developing the Ni–MH battery that was applied in some EVs, such as Toyota RAV4L, and Honda EV Plus.

3.2.2. Lithium-based batteries

Lithium-based systems opened a new era for high-energy and high-power batteries and more and more replace other battery technologies such as lead–acid and nickel-based systems. From the late 1960s, many battery technologies were explored and emerged because conventional aqueous batteries fail to satisfy the booming demands for portable energy storage (Demir-Cakan et al., 2019). Accordingly, a critical survey of EV batteries is given in Table 1 in various aspects of overall chemical reactions, key parameters, pros and cons as well as examples and EV applications (Chau, 2016; Garche et al., 2017).

Table 1
Critical survey of electric vehicle batteries.
Source: Data from Chau (2016) and Garche et al. (2017).

Types		Overall chemical reactions	Specific energy (Wh kg^{-1})	Specific power (W kg^{-1})	Life cycle	Pros	Cons	Examples and vehicle applications
Lead–acid		$Pb + PbO_2 + 2H_2SO_4 \leftrightarrow 2PbSO_4 + 2H_2O$	30∼50	150∼200	400∼800	Low cost, good performances in low and high temperatures	Low energy efficiency, low specific energy, memory effect	**VRLA**: Ford Ranger, Chrysler Voyager, Suzuki Alto
Nickel-based	Ni–Fe	$3Fe + 8NiOOH + 4H_2O \leftrightarrow 8Ni(OH)_2 + Fe_3O_4$	35∼80	150∼450	800∼2000	Low cost, high specific power	Low energy efficiency, low specific energy	**Ni–MH**: Toyota RAV4L, Honda EV Plus, Peugeot 106
	Ni–Cd	$2NiOOH + 2H_2O + Cd \leftrightarrow 2Ni(OH)_2 + Cd(OH)_2$						
	Ni–Zn	$2NiOOH + 2H_2O + Zn \leftrightarrow 2Ni(OH)_2 + Zn(OH)_2$						
	Ni–MH	$MH + NiOOH \leftrightarrow M + Ni(OH)_2$						
	$Ni–H_2$	$2NiOOH + H_2 \leftrightarrow 2Ni(OH)_2$						
Ambient-temperature lithium	Li-ion	[a]$LiYO_2 + C \leftrightarrow Li_xC + Li_{1-x}YO_2$	120∼300	200∼450	600∼>3000	High energy efficiency, high specific power, long life cycle	High cost (moderate), fire hazard (reliability)	**Li-Ion**: Tesla 3, BMW i3, Nissan Leaf
	Li-metal	[b]$xLi + M_yB_z \leftrightarrow Li_xM_yB_z$						
Sodium-beta	Na/S	$2Na + xS \leftrightarrow Na_2S_x$	115∼200	120∼250	800∼2000	High energy efficiency, high specific energy	High operating temperature, safety concern, high cost	**$Na/NiCl_2$**: BMW AG, Mercedes-Benz Vito
	Na/MCl_2	$2Na + MCl_2 \leftrightarrow 2NaCl + M$, (M = Ni, Fe)						
High-temperature lithium	Li/FeS	$2Li–Al + FeS \leftrightarrow Li_2S + Fe + 2Al$	130∼180	240∼400	1000∼1200			–
	Li/FeS_2	$2Li–Al + FeS_2 \leftrightarrow Li_2 FeS_2 + 2Al$						
Metal/Air		$4M + nO_2 + 2nH_2O \leftrightarrow 4M(OH)_n$, (M = Li, Zn, Al, Fe)	75∼250	100∼200	300∼800	Low cost, high specific energy, convenient refueling	High cost, low specific power, narrow operating temperature window	**Zn/Air**: Mercedes-Benz MB410, GM-Opel Corsa Combo
Zinc/Halogen	Zn/Br_2	$Zn + Br_2 \leftrightarrow Zn^{2+} + 2Br^-$	65∼75	60∼110	200∼400	Refuel liquid, low cost	Frequency maintenance, low specific energy and power, high cost	**Zn/Br_2**: Fiat Panda, Hotzenblitz EV, Toyota EV-30
	Zn/Cl_2	$Zn + Cl_2 \leftrightarrow Zn^{2+} + 2Cl^-$						

[a]$LiYO_2$ nominally represents $LiCoO_2$, $LiNiO_2$, $LiMn_2O_4$ and $Li_4Ti_5O_{12}$.
[b]M_yB_z is the transition metal material.

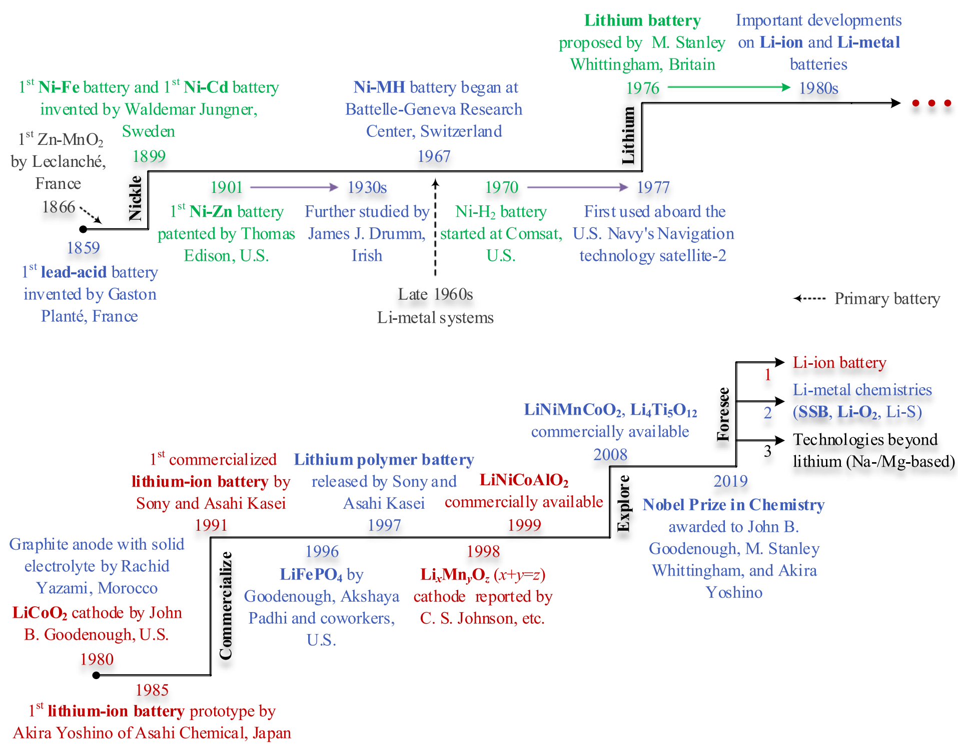

Fig. 6. Milestones and foresight of battery evolutions.

(1) Lithium-Metal Batteries

Experimentation on lithium batteries was started by G.N. Lewis in 1912 (Lewis and Keyes, 1912, 1913). As a primary LMB, it came much earlier than the LIBs in 1976. This LMB tried to use metallic lithium as its anode and the non-aqueous electrolyte. It brought technological breakthroughs by offering higher specific energy and larger energy density but with much lower weight, typically the coin-type Li/MnO_2 battery. Since the 1970s, a series of lithium-metal-based primary systems were developed by trying various cathode materials, such as iodine (I_2), manganese dioxide (MnO_2), pyrite (FeS_2), and many more (Eichinger et al., 1990a,b; Brandt, 1994).

The development of primary LMBs inspired further efforts in researching rechargeable LMBs. To seek new cathode materials, the innovation of intercalation materials by Whittingham was accepted as a key advancement for rechargeable lithium batteries (Whittingham, 1976, 2004). Currently, the rechargeable LMBs are faced with severe safety concerns and hence cannot achieve successful commercialization yet. Nevertheless, the Li metal has the significant advantages of the highest specific capacity of 3860 mAh/g and lowest operation potential of −3.04 V (Chen et al., 2019a). LMBs are potential candidates for EV propulsion due to their considerably high energy density and specific energy because of using a lithium metal anode. Even though there are various types of LMBs, such as lithium/sulfur batteries (LSBs) and lithium/oxygen batteries, and SSBs, which are typically based on a lithium metal anode and layered oxide cathode in combination with a solid electrolyte (solid polymers or inorganic solids) (Thackeray et al., 2012; Robillard, 2005), the SSBs are widely seen as the most promising technology to further boost the energy density for EV applications (Janek and Zeier, 2016). In contrast to liquid electrolytes, solid electrolytes can be widely recognized as an enabler for safe battery operation when using lithium metal anodes.

(2) Lithium-Ion Batteries

In the 1980s, Goodenough and collaborators opened a new era of the LIBs for power batteries. Fig. 6 (bottom) highlights the critical progress of LIBs, which is mainly classified into three crucial moments—commercialization since 1991, exploration since 2008, and foresight since 2019. The 1st generation of LIBs was based on $LiCoO_2$ and petroleum coke used as cathode and anode materials, respectively (Mizushima et al., 1980). The 2nd and 3rd generations of LIBs had further improvements concerning the anode material (hard carbon → graphite) and electrolyte, which resulted in further improvements in terms of energy density (Winter et al., 2003). The state-of-the-art cathode materials for high-energy LIB cells are the layered lithium nickel cobalt manganese oxides, such as $Li[Ni_xCo_yMn_z]O_2$ (abbreviated as NCMxyz) due to their increased capacities and reduced cost compared to $LiCoO_2$, while graphite is still the state-of-the-art anode material. The energy density and cost of LIBs can be further improved by increasing the cathode layered oxides' nickel-content (e.g., to more than 80%) and by adding silicon to the graphite negative electrode. NCM622 ($Li[Ni_{0.6}Co_{0.2}Mn_{0.2}]O_2$) and NCM811 can be considered as state-of-the-art materials for automotive applications, while the anode is still dominated by graphite and only a few cells apply silicon (in form of SiO_x) in small amounts (≤8 wt%). Several battery cells also used $LiMn_2O_4$ (LMO) as a blend cathode material in combination with NCM to adjust the power to energy ratio. However, given higher energy densities, LMO is more and more replaced by high-energy NCM materials. Despite their lower energy density, $LiFePO_4$ (LFP)-based LIB cells are becoming very popular for automotive applications due to their unsurpassed safety, high cycle life, and low cost (cobalt-free nature) (Yang et al., 2021).

LIBs were successfully improved from the specific energy of 98 Wh kg^{-1} in 1990 to 195 Wh kg^{-1} in 2008 and more today (Yamaki, 2009) and thus have been widely applied in HEVs and BEVs. Table 1 shows the performance, advantages, drawbacks, and EV applications of LIBs. For better identification, both the specific energies and the energy densities are quantitatively

Table 2
Overview of cells and batteries for electric vehicles.
Source: Data from Schmuch et al. (2018), Zhang et al. (2019a) and Li et al. (2020a).

Battery	Anode	Cathode	Nominal tension (V)	Specific energy (Wh kg^{-1})	Energy density (Wh L^{-1})	Capacity (Ah)	Charge (C)	Discharge (C)	Life cycle	Thermal runaway (°C)	Key features	Manufacturers	EV model	Battery energy (kWh)	Driving range (km)
Li-ion (Cobalt-rich)	C	LCO	3.7~3.9	150~200	-	-	0.7~1	1	500~1000	150	Mature	Sony	-	-	-
Li-ion (Cobalt-medium)	C	NCM	3.65~4.0	130~241	215 393 466	25 56 59	0.7~1	1	1000~2000	210	High energy	Panasonic/Sanyo LG Chem LG Chem	VW e-Golf (2015) Chevrolet Bolt (2016) Renault Zoe 50 (2017) VW ID.3 Pro S (2020) ByD Qin Pro EV NIO ES6 Standard BAIC EU5 R550	24 60 52 82 69.5 84 60.2	135~190 383 390 550 520 490 460
	C, Si or SiO-C, Si-C or SiO_x-C	NCA	3.6~3.65	200~310	673 673 683	3.2 3.4 4.75	0.7	1	500	150	High energy	Panasonic, SAFT, LG Chem	Tesla S (2012) Tesla X (2015) Tesla 3 (2017) Tesla Y (2020)	~100 ~100 ~75 75~100	595 525 500 480~595
	LTO	NCM NCA	2.3~2.5	89 70~85	200	20	1	10	3000~7000	-	Fast charge	Toshiba	Honda Fit EV (2013)	20	130
Li-ion (Cobalt-poor/free)	LTO	LMO													
	C	LNO	3.6~3.7	150~200	-	-	0.7~1	1	>300	150	Bad thermal stability	-	-	-	-
	C	LMO LMO-NCM, LMO-NCA-NCM, LMO-NCA	3.7~4.0 3.7 3.65 3.7 3.7 3.75 3.75	100~150 109 172 185 189 155 167	218 312 357 357 309 375	50 63 37 94 33 40	0.7~1	1	300~700	250	High discharge rate	LG Chem, GS, NEC, Yuasa Li Energy Japan Samsung SDI Samsung SDI AESC	Mitsubishi i-MIEV (2008) Fiat 500e (2013) VW e-Golf SEL (2016) BMW i3 (2017) Nissan Leaf (2015) Nissan Leaf S Plus	16 24 35.8 33~42.2 30 62	100~160 140 201 183~246 172 364
	C	LFP	3.2~3.3	90~130	-	-	1	1	1000~2000	270	Highly stable	A123, Valence Tech, BYD	Chevrolet Spark BAIC EC220	19 -	132 206
Li-metal	Li	O_2; S	-	-	-	-	-	-	-	-	Next generation	-	-	-	-

Year in bracket indicates start of production. C, graphite; Si, silicon; LCO (1st generation), $LiCoO_2$; LNO (2nd generation), $LiNiO_2$; LMO (3rd generation), $LiMn_2O_4$; LFP, $LiFePO_4$; NCM, $Li[Ni_{1-x-y}Co_xMn_y]O_2$ (e. g. $Li[Ni_{0.8}Co_{0.1}Mn_{0.1}]O_2$ or $Li[Ni_{0.6}Co_{0.2}Mn_{0.2}]O_2$); NCA, $Li[Ni_{1-x-y}Co_xAl_y]O_2$ (e. g. $Li[Ni_{0.8}Co_{0.15}Al_{0.05}]O_2$); LTO, $Li_4Ti_5O_{12}$.

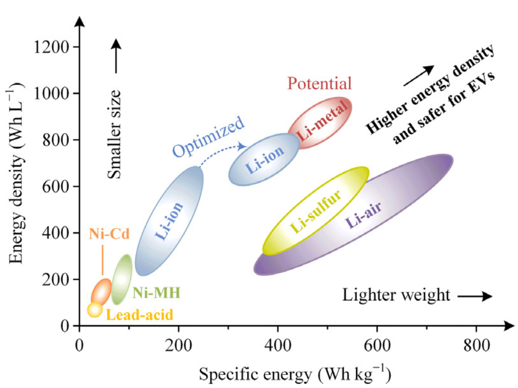

Fig. 7. Specific energy and energy density of various batteries at cell level.

compared in Fig. 7 (Tarascon and Armand, 2011; Placke et al., 2017), where the LIBs are with higher energy density and higher specific density than the battery technologies before lithium. Fig. 8 shows a more comprehensive comparison among lithium-based batteries (Placke et al., 2017; Hannan et al., 2018; Zhang et al., 2019a; Doughty and Roth, 2012). At the current stage, lithium titanate technology using a spinel $Li_4Ti_5O_{12}$ anode is not considered for high-energy batteries and long driving ranges by electrochemistry specialists, but it can be considered as an alternative technology, especially when fast charging is needed (e.g., in electric buses; see Toshiba SCiB™ technology) (Toshiba, 2022; Nemeth et al., 2020). An overview of various cells and batteries for EVs is listed in Table 2 (Schmuch et al., 2018; Zhang et al., 2019a; Li et al., 2020a). As cobalt can be regarded as one of the strategic and "critical" resources, the LIBs are classified into three classes—cobalt-rich, cobalt-medium, and cobalt-poor/free. On top of anode and cathode materials, all detailed specifications, manufacturers, and EV models are also summarized in Table 2.

Interactively, the popularization of EVs will express an increasing requirement on batteries' KPIs, especially energy density, fast charging, and safety, which will generate a powerful motivation to search for novel materials for LIBs and to look for advanced technologies beyond lithium.

3.2.3. Battery technologies beyond lithium

Since LIBs may inevitably reach their intrinsic limits on specific energy and energy density, battery technologies beyond lithium have been intensively investigated in the last decades. Wherein, three types of batteries are deemed as alternative technologies as follows.

(1) Metal/Air Batteries

Metal/air batteries use the metallic anode and the air cathode, and their energy capacities are limited by the anode capacity and the handling procedure. Nonetheless, they can offer a very high specific energy and energy density of up to 600 Wh kg^{-1} and 400 Wh L^{-1}, respectively, With different metallic anodes, the metal/air batteries include the zinc/air, aluminum/air, iron/air, magnesium/air, and calcium/air types besides the lithium/air counterpart (Yu et al., 2017). They can be manufactured into primary, electrically rechargeable, and mechanically rechargeable batteries, wherein mechanically rechargeable batteries are convenient for refueling and recycling. However, these rechargeable batteries suffer from the main drawbacks of low specific power and carbonation of alkaline electrolytes (Wang and Xu, 2019; Tan et al., 2021). Among this family, zinc/air battery (Sun et al., 2021a) was not mature but promising.

(2) Sodium-Beta Batteries

Sodium-beta batteries are renowned for their high energy densities, but only two technologies, including (i) sodium/metal chloride (Na/MCl_2) and (ii) Sodium/sulfur (Na/S) batteries, were successfully manufactured by researchers. To offer the ionic conductivity, they must operate at a high temperature of up to 270 °C∼350 °C.

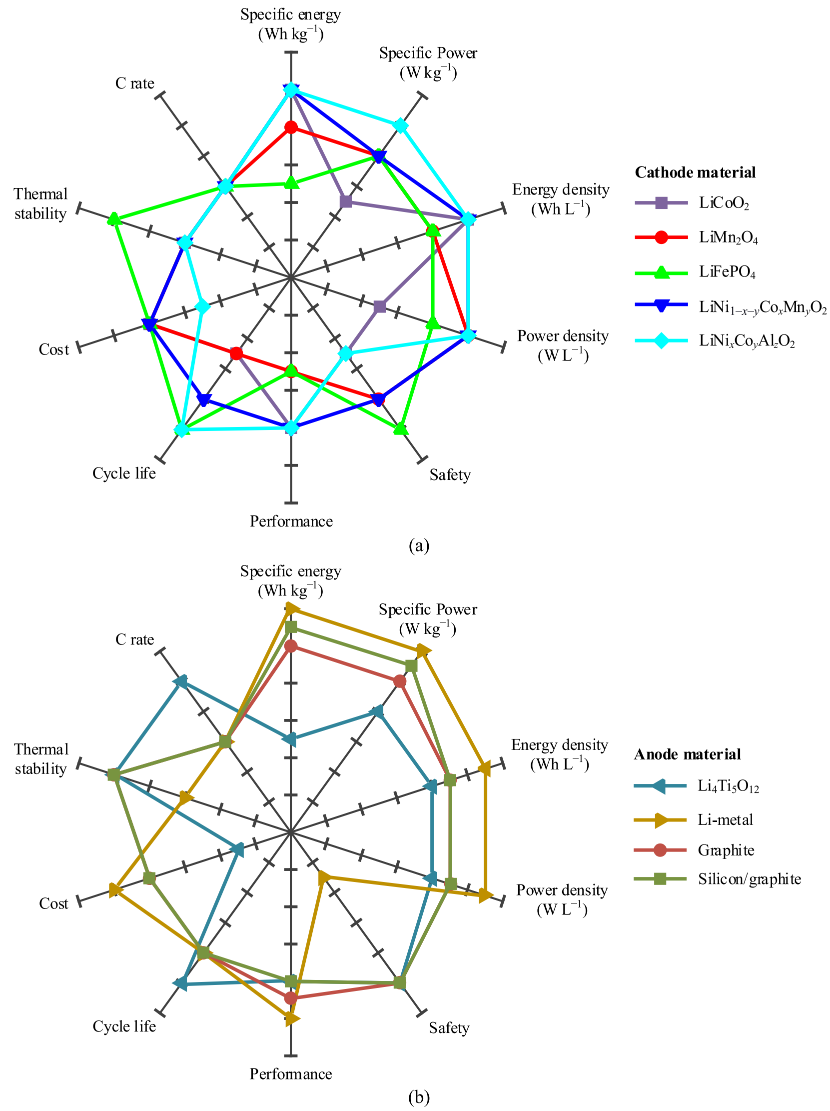

Fig. 8. Comparison of lithium-ion and lithium-metal battery materials. (a) Cathode material. (b) Anode material.

***a*. Sodium/metal chloride battery:** The cathode material of Na/MCl_2 battery adopts the transition metal chloride. The iron chloride and the nickel chloride are used to generate two types of batteries—$Na/FeCl_2$ and $Na/NiCl_2$, respectively, where the former has got more developed than the latter (Li et al., 2016; Sudworth, 2001). The $Na/NiCl_2$ battery has the advantages of wider operating temperature, less metallic material corrosion, and higher power density.

***b*. Sodium/sulfur battery:** Na/S battery adopts the sulfur cathode, sodium anode, and beta-alumina ceramic electrolyte. As listed in Table 1, sodium pentasulfide is generated from the reaction of the sulfur anode and sodium ion. The performance of Na/S battery degrades with the increasing internal resistance, which is worsened with the incremental depth of discharge. Recently, room-temperature Na/S battery was explored with high capacity and stable cycling performance (Wei et al., 2016; Xu et al., 2018).

(3) Alternative Batteries

Relevant battery technologies beyond lithium are related to various chemistries including zinc (Zn-)/sodium (Na-)/magnesium (Mg-)based chemistries among others. The production and commercialization of alternative ion batteries, in particular SIB, will be potentially scaled up soon.

***a*. Sodium-ion battery:** SIB has attracted intensive investigations since 2010, and numerous anode and cathode materials have been discovered (Yabuuchi et al., 2014). Wherein, the ambient-temperature SIBs exhibited two new energy densities of 163 Wh kg^{-1} and 210 Wh kg^{-1} at cell level (Senthil et al., 2022; Hwang et al., 2017), slightly lower than the high-energy LIBs. Nevertheless, the SIB is considered as an alternative because sodium occupies abundant resources on earth and exhibits similar chemistry to LIBs (Slater et al., 2013). The SIB's KPIs can be improved by choosing the electrode materials, such as carbonaceous materials, and intermetallic and organic compounds for anode materials. Electrolytes, additives, and binders are also quite important. Both the cell design and the electrode balancing challenge the further development of SIB.

***b*. Zinc-ion battery:** Recently, zinc-ion battery (ZIB) rekindles the research interests. The mild aqueous electrolyte endowed the ZIB with new vitality in energy storage systems and portable electronics (Konarov et al., 2018). It provides an acceptable energy density and owns the intrinsic advantages of safety, environmental benefit, and economy. However, some drawbacks associated with the ZIB are still unsolved. One of the key technologies is to search for suitable cathode materials for the intercalation of zinc ions (Song et al., 2018).

Very recently, aqueous ZIB adopted MnO_2 as the cathode material and is considered as a reversible Zn–MnO_2 battery. By focusing on the electrolytic mechanism, the Zn–MnO_2 redox flow batteries were recognized as promising candidates for large-scale static energy storage (Xue and Fan, 2021). A new electrolytic Zn–MnO_2 system was proposed to achieve a record high voltage of 1.95 V, a gravimetric capacity of about 570 mAh g^{-1}, and an energy density of around 409 Wh kg^{-1} (Chao et al., 2019). Another secondary Zn–Mn battery with near-neutral electrolytes was developed by using highly active Mn_3O_4@carbon nanowires, which showed superior performance in reversibility, capacity, and cycling durability (Ma et al., 2018). On the other hand, two kinds of aqueous Zn–V_2O_5 batteries were developed with high energy density and long cycle life (Zhang et al., 2018a; Hu et al., 2017), which are promising for stationary energy storage.

***c*. Magnesium-ion battery:** Due to low cost, superior safety, and environmental friendliness, magnesium-ion battery (MIB) was believed as an alternative to LIBs by some researchers, especially for stationary and mobile energy storage (Guo et al., 2021; Johnson et al., 2021). Magnesium is more abundant than lithium, around 2.3 wt% of earth's crust. An iron chalcogenide (FeS_2) nanomaterial cathode enhanced the reversible capacity for the MIB with a copper current collector (Shen et al., 2021). The MIB may offer high specific energy and specific power but still require a long journey to make a technical breakthrough (Li et al., 2018).

3.3. Emerging battery technologies

While LIBs dominate the market of high-energy-density applications, a variety of emerging battery technologies exist for various application purposes, such as lithium metal technologies, sodium-ion technologies, and other promising technologies.

3.3.1. Lithium metal technologies

(1) Lithium/Air and Lithium/Sulfur Batteries

Lithium/air (Li–O_2) battery can be classified into four categories by electrolytes: (i) nonaqueous; (ii) aqueous; (iii) hybrid aqueous/nonaqueous; and (iv) solid-state. The Li–O_2 battery with nonaqueous electrolytes can reach an extremely high specific energy ($\sim$11,700 Wh kg^{-1}) theoretically, thus being competitive to gasoline (Yu et al., 2017; Bruce et al., 2012). The aqueous one has a high risk of battery burning but its decomposition voltage is relatively low. The hybrid aqueous/nonaqueous one merges the advantages of two electrolytes. Great efforts have been devoted to identifying the inducements and searching for probable approaches to improve the round-trip efficiency and cycle life for Li–O_2 batteries, especially for electrode protection (Huang et al., 2020b). Nevertheless, many researchers recognized that Li–O_2 is a very challenging system and considered that many years of fundamental research are mandatory to bring this technology to application. Because sulfur has the features of high gravimetric capacity and low cost, remarkable advances have been made on the LSB for realizing its high energy density since the 1960s (Bhargav et al., 2020). Nevertheless, the sulfur-based cathodes suffer from poor electronic conductivity. Plus, special multielectron reaction mechanisms and soluble lithium polysulfide intermediates hinder the LSB from commercial applications (Huang et al., 2020a). Some researchers still believed that the LSB is promising for high-energy electric and hybrid propulsion (Zhao et al., 2020).

(2) Solid State Batteries

The SSBs with lithium metal anode have been identified as one of the most promising candidates (Deng et al., 2021) because of the boosted energy density and safety. Whereas, its Coulombic efficiency is low, which prohibits its practical application. A high-performance SSB was proposed with a sulfide electrolyte, and the use of a thin silver–carbon (Ag–C) layer contributes to a long electrochemical cyclability (Lee et al., 2020). Furthermore, both the high energy density of over 900 Wh L^{-1} at material level (Placke et al., 2017) and the high Coulombic efficiency of over 99.8% can be achieved experimentally. Nevertheless, its cycle life is only 1000 times, which is not preferable for EV applications. The SSBs are relatively stable, but the interfacial charge-transfer process is another major issue. On the other hand, the high-capacity requirement in EVs may challenge the SSBs using ceramic or polymeric electrolytes (Schmuch et al., 2018).

3.3.2. Sodium-ion technologies

The Chinese battery manufacturer CATL has unveiled the first generation of SIB developed as an alternative to LIBs, offering an energy density of up to 160 Wh kg^{-1} and which can be charged to 80 percent in 15 min at room temperature. For the next generation of SIBs, CATL researchers aim for an energy density of 200 Wh kg^{-1} or more (CATL, 2021). Compared to LIBs, SIBs have a poorer energy density—both in terms of weight and volume. However, cheaper raw materials costs, as well as more abundant sodium resources in the Earth's crust, are proposed as major advantages of SIBs. Their reduced energy density tends to exclude them from powering long-range EVs so that SIBs are mainly intended for low-speed EVs (such as bus) as well as low-end energy storage solutions.

3.3.3. Other promising technologies

Dual-ion battery (DIB) (Placke et al., 2018) and dual-carbon battery (DCB) (Jiang et al., 2019b) are promising for stationary energy storage instead of traction batteries for EVs. Dual-graphite/carbon battery is a subcategory of DIB. A new aluminum–graphite DIB was reported to show high reversibility and high energy density (Zhang et al., 2016). A dual-carbon-based potassium dual-ion battery was checked with relatively good comprehensive performance (Zhu et al., 2018). Considering the self-discharge, poor safety, low Coulombic efficiency, and insufficient energy density, the ongoing progress of both carbon materials and new electrolytes will accelerate the upgradations of DIB and DCB (Chen et al., 2020b).

4. State-of-the-art battery management

4.1. Fundamentals

A whole on/off-board charging system for EVs is sketched in Fig. 9. The conventional charging systems usually include adaptors and plug-ins. Each EV charger typically consists of one alternating current (AC)/direct current (DC) converter with an optional power factor correction (PFC) and one DC/DC converter with a unidirectional or bidirectional power flow, as shown in Fig. 10(a) and (b), respectively (Mohammed and Jung, 2021; Tu et al., 2019). The use of a high-frequency (HF) transformer is for high-efficiency DC/DC conversion with reliable isolation. When the EV parks for charging, the AC electric power can be transferred to the battery pack through the AC/DC converter. The electric machine can gain energy from the battery pack with the help of BMS and power converters. During the V2V, V2H, and V2G operations, the battery energy can be fed back to the power grid or transferred to other EVs, thus coordinating with the smart

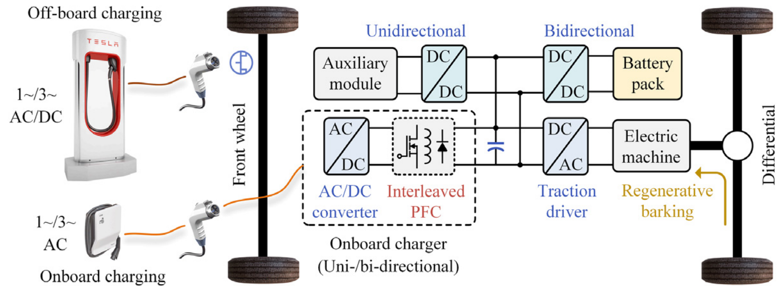

Fig. 9. On-/off-board charging system for electric vehicles.

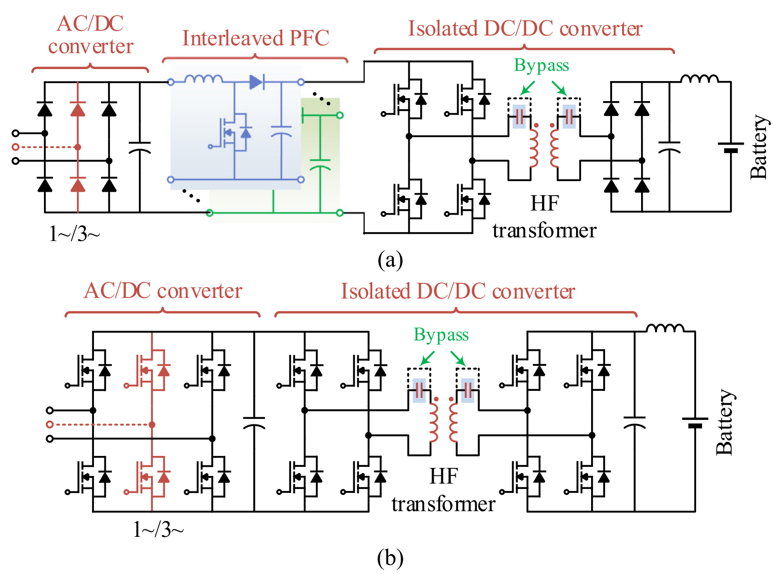

Fig. 10. Typical charging topologies for electric vehicles. (a) Unidirectional charger. (b) Bidirectional charger.

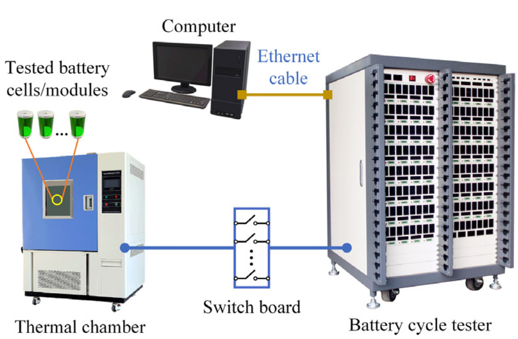

Fig. 11. Systematic configuration of battery test bench.

grid and performing the wireless energy trading among vehicular peers.

To obtain detailed battery information, a battery testing system is commonly used for periodical experimentations in Fig. 11. It comprises a battery cycle tester, a computer for user interface and data collection, a thermal chamber, and battery cell(s) or module(s). Various tests can be performed under given temperatures (Hu et al., 2012). After data acquisition from tests, a battery model can be established, and some algorithms can be applied for battery state estimations. The AC impedances at different frequencies are acquired by electrochemical impedance spectroscopy (EIS), and its Nyquist plot may help choose a proper model.

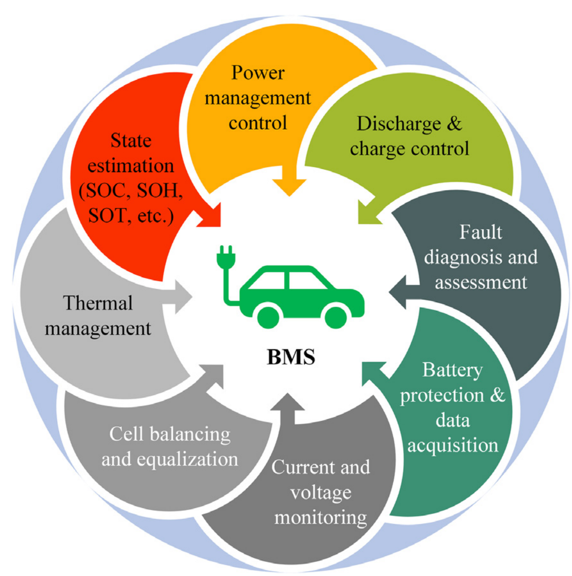

Fig. 12. Advanced battery management system.

A BMS in each EV can prevent a battery pack from experiencing a physical damage, performance degradation, and thermal runaway (Zhai et al., 2020; Lin et al., 2020; Han et al., 2020). In Fig. 12, a BMS integrates a series of advanced functions (Hannan et al., 2018; Liu et al., 2019), wherein the battery modeling and

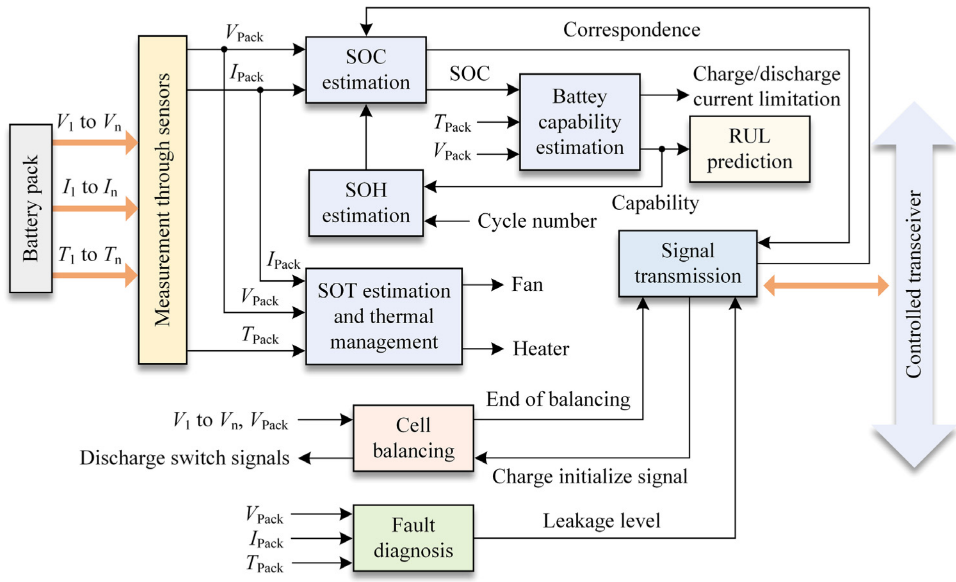

Fig. 13. Functional block diagram of battery management system for electric vehicles.

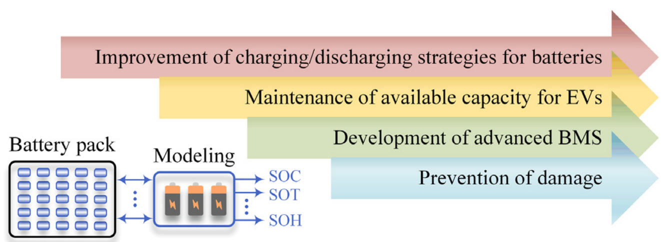

Fig. 14. Significances of battery modeling.

the state estimation are fundamental but critical (Wang et al., 2017). Accordingly, a block diagram of the BMS is depicted in Fig. 13 (Hannan et al., 2017). A sensing block measures the battery parameters at different locations and generates digital signals. These recorded parameters are used to estimate the battery states. The battery thermal management is performed to (in)activate the fan or heater, thus managing the temperature in an optimal range. With suitable algorithm(s), a capacity estimation block produces the charge/discharge current limitations. Multi-dimensional limitations restrict the irregularities of overcharge/-discharge by a cell equalizer. A fault diagnosis block is in charge of safeguarding battery safety. Finally, a controlled transceiver block is to control the information flow for sending and receiving data.

4.2. Advanced management technologies

4.2.1. Battery modeling

Model accuracy may directly affect the precision of state estimation, such as for the state of charge (SOC), state of health (SOH), and state of temperature (SOT) (Xie et al., 2020a; Hu et al., 2021). Thus, battery modeling turns into one of the most significant prerequisites for BMSs (Tamilselvi et al., 2021). Fig. 14 concludes the main significances of battery modeling. To represent EV batteries, three modeling methods, including (i) electrochemical models (Miguel et al., 2021; Kim et al., 2021), (ii) equivalent circuit models (Hu et al., 2012; Zhang et al., 2014b), and (iii) data-driven models (Dong et al., 2015; Shen et al., 2020), are elaborated in this section.

(1) Electrochemical Model

A battery can be modeled via physics-based approaches that offer a good consistency with its external characteristics (Zhou et al., 2021). Thanks to the simplicity, the single-particle model becomes one of the most mature models in Fig. 15 (top) (Tamilselvi et al., 2021; Fotouhi et al., 2016; Romero-Becerril and Alvarez-Icaza, 2011), but its accuracy is relatively low. A single particle model with electrolyte dynamics was developed and exhibited a good adherence to real parameters (Pozzi et al., 2019). Considering a more realistic scenario, a pseudo-two-dimensional model was adopted to simulate the battery behaviors (Doyle et al., 1993). Influences of liquid/solid phase concentration and phase potential could be expressed by a couple of partial differential equations. To solve these equations, the focus was to simplify the relevant models (Han et al., 2015). Recently, a reduced-order electrochemical model was devised to offer a high fidelity yet low computational cost (Li et al., 2021a), but its over-dependence on numerous variables increased the complexity and hindered the applicability, especially considering the battery temperatures and aging. Hence, online parameter identification was applied to improve the model applicability (Wang et al., 2021).

The electrochemical models represent the cores of batteries at a microscopic scale based on the nonlinear electrochemical reactions. Such kind of models delivers the most accurate information about batteries, but its main barriers are owing to two objections: (i) A wealth of non-analytical equations require to be solved via global optimization, and (ii) the strong coupling exists between the control equations and boundary conditions (Zhou et al., 2021). Moreover, the optimization approaches may become large memory cost and computational burden, and their convergence rate deserves concern. Combining the thermal and electrochemical equations, a thermal-electrochemical model became a recent research focus (Li et al., 2021f).

(2) Equivalent Circuit Model

To improve the model applicability, some researchers move forward to investigate the equivalent circuit models (ECMs) that use the basic electrical components to imitate the battery behaviors. As the lumped models, two types of ECMs are more straightforward to solve for power flow control in BMSs.

***a*. Integral-order model (IOM):** Fig. 16 shows some basic ECMs of one battery (Wang et al., 2016a), where partial ECMs can be classified as the IOMs. Typically, in Fig. 16(a), the simplest

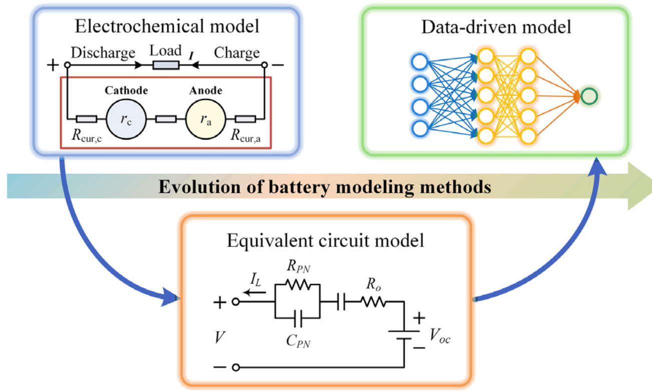

Fig. 15. Evolutions map of battery modeling methods.

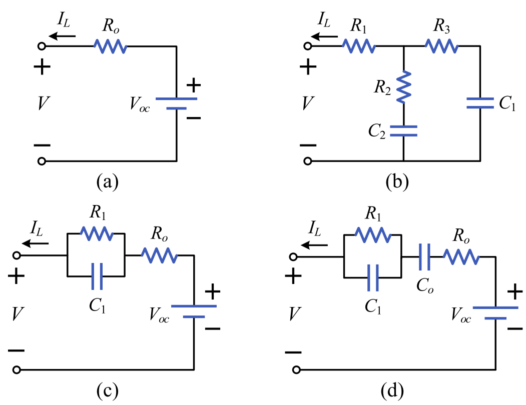

Fig. 16. Basic equivalent circuit models of electric vehicle batteries.

form of Rint model consists of an ideal voltage source in series with resistance (Johnson, 2002), but it fails to exhibit the internal polarization phenomenon. Based on this Rint model, a Thevenin model was proposed by adding a parallel-connected resistor–capacitor (RC) tank (Ding et al., 2019) in Fig. 16(c). Fig. 17(a) and (b) show the advanced ECMs of an IOM and a fractional-order model (FOM), respectively. In Fig. 17(a), two or more RC tanks are added to better reflect the dynamic characteristics of one battery (Yao et al., 2015; Xia et al., 2017). The IOMs have advantages of faster simulation speed and fewer model parameters, but they mainly suffer from unreliable extrapolation and fail to predict the internal electrochemical states. The use of more RC tanks ensures higher estimation accuracy but leads to more difficult parameter identification. Thus, a tradeoff shall be made among the model accuracy, complexity, and computing burden.

***b*. Fractional-order model (FOM):** The use of pure RC tanks fails to present the electrochemical characteristics on the whole frequency range, especially for the middle frequencies. As a typical FOM in Fig. 17(b), the constant phase elements were used to replace the pure capacitive elements (Liu et al., 2021d). The FOMs are capable of fitting the whole frequency range and possess higher accuracy in representing the physical phenomena. Nonetheless, they suffer from a slower simulation speed and a more complicated structure. After choosing a proper ECM, the model parameters need to be determined via various approaches, where both the EIS and Bode plot are most classical (Ruan et al., 2021). Fig. 18 shows the EIS outline of a typical LIB cell (Zou et al., 2018b).

(3) Data-Driven Model

Fig. 15 shows the evolution map of battery modeling methods from the electrochemical model and the ECM to the data-driven model (Tamilselvi et al., 2021; Wu et al., 2020). Some data-driven models have been recognized as more adaptable and efficient. They evolved from the external characteristics of batteries and hold a good adherence to the nonlinear electrochemical reactions. Such black-box models can build up a mathematical model or figure out the weight parameters by using the training data only. They can readily extract the hidden information and own a good generalization ability for battery state estimation (Zhou et al., 2021). As one data-driven model, the machine learning (ML) approaches were actively developed and achieved fruitful results, such as using support vector machines (Yao et al., 2021), artificial neural networks (NNs) (Lindgren et al., 2016), and long- short-term memory networks (Ren et al., 2021). Besides, a three-dimensional active Monte Carlo model was studied to describe the internal mechanisms and reactions, thus revealing the mesostructural evolutions (Thangavel et al., 2020).

Table 3 provides a comprehensive comparison of three modeling methods (Zhang et al., 2014b; Liu et al., 2021d; Jaliliantabar et al., 2022). The data-driven models have superior performances in accuracy and robustness over their counterparts, especially considering the temperature and aging effects. However, the data-driven approaches can be easily influenced by the selection of training datasets and intelligent algorithms. Plus, the implementation time of relevant algorithms ought to be taken into full consideration. Currently, the data-driven model is very promising and is expected further breakthroughs.

4.2.2. Battery state estimation

Battery state estimations mainly fall into three approaches: (i) direct estimation method, (ii) model-based method, and (iii) data-driven method. First, direct estimation methods generally include the look-up table approach and the direct measurement approach. Second, model-based methods can be further divided into (i) filter-based methods, such as Kalman filter (KF) and particle filter (PF), and (ii) observer-based methods, such as Luenberger observer, sliding mode observer, H-infinity/H∞ observer. Third, data-driven methods can embrace the technologies of ML, NN, and deep learning for battery state predictions, especially the internal temperature distribution.

(1) Direct Estimation Method

The direct estimation method is straightforward and readily implemented (Wang et al., 2020). An open-circuit voltage (OCV) estimation method was presented with a detailed implementation process (Ali et al., 2019). The OCV was measured to establish an offline table and look up the SOC in a simple but accurate way (Klintberg et al., 2019; Xing et al., 2014). Nevertheless, the hysteresis characteristic of batteries may cause the differences of measured parameters and thus the estimation errors (Dong et al., 2016), which is not acceptable for aviation or military

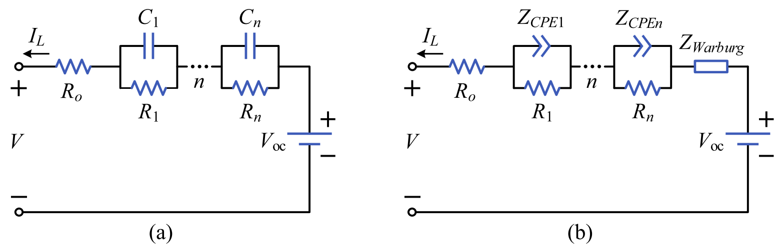

Fig. 17. Advanced equivalent circuit models of electric vehicle batteries. (a) Integral-order model. (b) Fractional-order model.

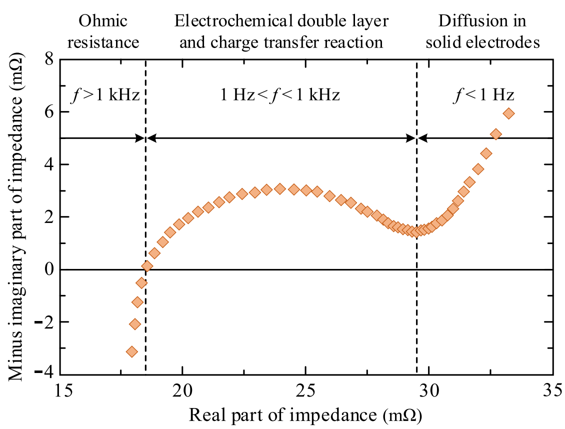

Fig. 18. Electrochemical impedance spectrum of typical lithium-ion battery cell.

applications desiring high precision. By using the battery current and voltage, the internal resistance can be calculated to estimate the SOC, SOH, capacity, etc. (Laadjal and Cardoso, 2021; Ling and Wei, 2021). However, the internal resistance is very low (Lu et al., 2013), and the measurement precision is hardly ensured. Besides the electromotive force of batteries (Waag and Sauer, 2013), the EIS was used to realize the state estimation for LIBs (Mc Carthy et al., 2021; Wu et al., 2018). To calculate the SOC, an ampere-hour integral method was more straightforward (Zhang et al., 2014c), but its error will be accumulated with the sensor errors in an open-loop estimation. Furthermore, aging and temperatures may degrade the estimation accuracy because of deviations of initial capacity and Coulomb efficiency. To obtain the SOT, temperature sensors were directly embedded into the cell internal layers for measurements (Lee et al., 2017), such as using the thermocouples (Zhang et al., 2014a), resistance thermometers (Wang et al., 2016b), and fiber Bragg-grating sensors (Raijmakers et al., 2019) as temperature indicators. However, this methodology would bring larger assembling difficulties and safety issues. Consequently, this direct estimation method is often joined with other methods to improve the estimation precision and reliability.

(2) Model-Based Method

Both the filter-based methods and observer-based methods aim to ensure higher precision and better robustness. Their precision highly depends on the model's accuracy and is at the expense of a high computational cost. The KF techniques have been used to estimate the battery states including SOC, SOH, SOT, and remaining useful life (RUL). An intelligent adaptive extended KF was developed to handle the distribution change add improved the accuracy (Sun et al., 2021b). Incorporating a Thevenin ECM, an adaptive square root extended KF was devised to deal with the filtering divergence and validated under a dynamic temperature range (Jiang et al., 2021). Besides, an adaptive cubature KF was identified with excellent abilities of generalization and convergence and reduced the design complexity effectively (Tian et al., 2020). Since the estimator deviation grows with battery life, an adaptive unscented KF refreshed the noise covariance for SOH and RUL estimations (Xue et al., 2020). With the help of KF, thermal models were developed to predict the surface and internal temperature distributions (Xie et al., 2020b; Dai et al., 2015). Promisingly, based on an electrothermal model, a novel extended KF was designed to estimate both the surface and internal temperatures of batteries without additional temperature sensors (Pang et al., 2021). On the other hand, the PF method can also realize the state estimations, in particular, it is featured to solve the nonlinear and non-Gaussian problems, thus suitable for battery health prognosis. A model-oriented gradient-correction PF was developed to foresee the aging trajectories of LIBs with a reduced sensitivity (Tang et al., 2019). Jointly, a novel extended Kalman PF was reported with higher precision for RUL prediction, in which the PF was optimized by an extended KF (Duan et al., 2020). Besides, a multi-model PF was recommended to achieve the multi-step-ahead estimation of capacity and RUL, which narrowed down uncertainties and gave stable forecasts (Li et al., 2021b). Finally, a second-order central difference PF was suggested for both SOH and RUL predictions (Chen et al., 2020a).

Moreover, the aforementioned observers have been explored for state estimation (Sun et al., 2020a). The key is to design the gains for observers. First, a fractional-order estimator was designed, where the Luenberger observer ensured the nominal error convergence, while the sliding mode observer improved the robustness to uncertainties (Zou et al., 2018a). Second, upon a hybrid battery model, a proportional-integral observer was developed to predict the SOC purposely (Feng et al., 2020). Third, an H-infinity observer was studied based on a fractional-order ECM to reveal the electrochemical impedance for SOC estimation (Chen et al., 2020c). Besides, some other observers, such as nonlinear observers (Liu et al., 2021e), were also investigated accordingly. Practically, all these methods are still expected to further minimize the estimation errors and improve the robustness to uncertainties while not causing a heavy computational burden.

(3) Data-Driven Method

Data-driven method intends to treat a battery system as a black box. Instead of analyzing the electrochemical mechanism

Table 3
Comparison among three battery modeling methods.

Modeling methods	Accuracy	Interpretability	Complexity	Main applications
Electrochemical model	Medium	Low	High	Battery design
Equivalent circuit model	Medium	High	Low	Estimation of SOC and state of power (SOP)
Data-driven model	High	Low	Medium	Estimation of SOT, SOH, and RUL

and building the model, it attempts to extract the hidden correlations from numerous trained data (Hu et al., 2020b) and form a predictive model directly. Several data-driven methods are commonly used for battery state estimation, such as ML (Roman et al., 2021; Fei et al., 2021) (including the NN Tang et al., 2020; Li et al., 2021c and support vector machine Yao et al., 2021; Feng et al., 2019), genetic algorithm, and so on. All these methods have been actively explored to predict various performance indexes, in particular, the SOH, RUL, and capacity degradation. Typically, a data-driven electrothermal battery model is shown in Fig. 19 (Fei et al., 2021; Attanayaka et al., 2021; Zhu et al., 2019; Kleiner et al., 2021), which is the main research model. It is expected to provide an accurate prediction including capacity, RUL, and internal temperature. Besides, such a model will join the charging control and perform new control strategies, such as maximum current charging, most healthy charging, and shortest time charging rather than the constant-current and constant-voltage charging (Liu et al., 2021a).

Besides the SOC estimation (Deng et al., 2020), early predictions of capacity degradation, SOH, and RUL are critical to guard against battery malfunctions and traffic accidents (Li et al., 2019). First, a data-driven model using the ML was developed to predict the battery cycle life effectively (Severson et al., 2019). By using the least-square support vector machine and the model-based unscented PF, an online joint data-driven estimation was investigated with a suppressed SOH error of below 4% (Song et al., 2020). An efficient data-driven SOH estimator was effectively optimized by using the nondominated sorting genetic algorithm II (Cai et al., 2020). Furthermore, an ML pipeline was designed and evaluated for capacity fade prediction (Roman et al., 2021). For the early-cycle prediction of RUL, an ML-based framework was reported with three parts: (i) feature extraction, (ii) feature selection, and (iii) ML-based prediction, and it substantially decreased the prediction errors (Fei et al., 2021). Incorporating both the transfer learning, a pruned convolutional NN method was developed to achieve fast capacity estimation by using a small dataset only (Li et al., 2021c). Nonetheless, many issues may add to the prediction difficulty in terms of variable operating conditions, battery cell imbalances, and cells aging unevenly. These issues will challenge the accuracy of battery pack prediction.

A comprehensive comparison of various estimation methods is summarized in Table 4 in terms of their types, pros and cons (Wang et al., 2020; Ali et al., 2019; Hu et al., 2020b). In a nutshell, the precision and robustness of direct estimation methods are not acceptable outside the laboratory. The model-based methods highly depend on the model accuracy, computational resources, and sufficient experimental data. Trained by a large amount of data, the data-driven methods have the advantage of insensitivity to the model's accuracy and operating conditions. Its development trends are widely acknowledged to reduce the computational burden and accelerate the processing rate. Besides, The CC and blockchain technology will be the most promising alternatives to reach these goals by fully leveraging and sharing the resources and data.

4.2.3. Safety issue and fault diagnosis

In the realm of BMS, thermal management, battery cell balancing, and fault diagnosis are significant for more reliable operations (Zhang et al., 2018b; Xiong et al., 2020a). Real-time online diagnosis can be deemed as one of the most significant concerns on intelligent battery management, especially for autonomous EVs.

(1) Thermal Management

Abnormal temperatures may degrade the battery capacity and shorten the service life. Thus, thermal management is a crucial requirement in various EVs, especially for improving the

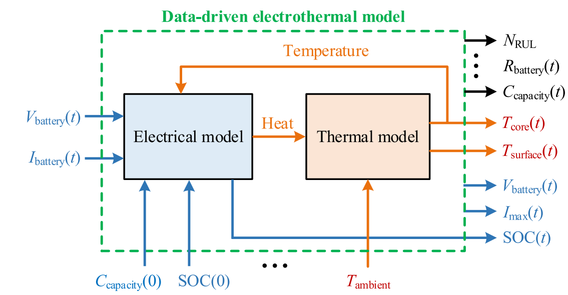

Fig. 19. Data-driven electrothermal battery model.

performance and safety of battery packs. Typical methods for cooling and preheating are summarized in Fig. 20, and their principles, pros and cons were comprehensively discussed in Zhang et al. (2022) and Wang and Du (2021). The purpose of a battery thermal management system (BTMS) is to ensure the battery working within a suitable temperature range, such as 20 °C∼40 °C for LIBs typically (Yi et al., 2022; Jilte et al., 2021). Over-low temperatures will induce the LIBs to grow lithium dendrites, thus possibly causing a short circuit, starting failure, and other malfunctions (Zhang et al., 2022). Also, the increase of internal resistance and the inactivity of electrochemical reactions may give rise to performance degradation. Over-high temperatures will result in battery thermal runaway, leading to a catastrophic failure, such as combustion and explosion. Also, the temperature non-uniformity within a battery pack will cause local degradation and faster aging (Rao and Wang, 2011). Therefore, the BTMS ought to regulate the temperature and ensure temperature uniformity among battery cells (Wang et al., 2016a). Recently, a new liquid cooling plate was embedded with the phase change material (PCM) to offer an economic and modular solution for the BTMS (Akbarzadeh et al., 2021). Coupled with the PCM and liquid cooling, another BTMS was designed to enhance the cooling effects by optimizing the coolant flows (Yi et al., 2022).

(1) Cell Balancing

Differences in reactions and manufactures may cause inconsistency among cells in terms of voltage, SOC, capacity fade rate, and aging rate (Das et al., 2020). In the worst cases, it may cause leakage, explosion, or fire. Hence, Cell voltage equalization is highly significant. Cell balancing technologies can be separated into two directions: (i) passive cell equalizer using a simple resistive circuit, and (ii) active cell equalizer using a complex control and circuitry (Trimboli et al., 2022). Typical representations are shown in Fig. 21, where the passive cell equalizers suffer from heat issues and low efficiency, while the active counterparts are highly efficient but increase complexity (Omariba et al., 2019). Besides, a switched-capacitor cell balancing circuit (Ye and Cheng, 2018) and a modular cell-balancing architecture (Trimboli et al., 2022) were developed for less loss and better stability. A symmetrical switched-capacitor structure was optimized to maximize the current paths and thus offered faster cell voltage equalization (Singirikonda and Obulesu, 2021). Furthermore, the software system, comprising suitable controllers and algorithms, is another crucial part to control the cell equalizers. The cell balancing algorithms mainly has three types: (i) voltage uniformity method, (ii) capacity uniformity method, and (iii) SOC uniformity method those are commonly used (Ouyang et al., 2018b,a).

(2) Fault Diagnosis

Fault diagnosis is another vital function of BMSs in EVs. The fault types are numerous, such as sensor fault, internal/external short-circuit fault, BTMS fault, overcharge/over-discharge fault and actuator fault (Xiong et al., 2020a). For fault diagnosis, various advanced and emerging methods are sorted out in Fig. 22 (Lu

Table 4
Comparison of state estimation methods for electric vehicle batteries.

Method	Pros	Cons
Direct estimation method Open circuit voltage Internal resistance Electromotive force Impedance spectroscopy Embedding sensors	Direct and simple method for implementation Low computational cost Easy combination with model-based method	Off-line estimation Long resting time Not accurate in practice Sensitive to sensor accuracy
Model-based method Filter-based method (e.g. Kalman-filter, particle filter) Observer-based method (e.g. Luenberger observer, sliding mode observer, H-infinity/H∞ observer)	Online and real-time Insensitive to initial state Not limited to system type Fast convergence High precision Robust to sensor noise	Precision depends on model accuracy High computational cost Require more experimental data and validation
Data-driven method Machine learning Neural network Support vector machine Genetic algorithm Fuzzy logic	Less pre-test required High estimation precision Independent of model Robust to conditions and noises	Depend on training samples High computational cost Requirements on efficiency and portability of algorithm
Cloud computing Vehicular cloud computing technology	Run complex algorithms Collaborate with cloud computation center Leverage resources of participating vehicles	More complicated due to high mobility and wide range of vehicles Possibly leak information and compromise privacy
Blockchain technology Private blockchain Consortium blockchain	Public ledger system Data sharing and tracking Protect user privacy More driving data	Not mature technology Some research gaps (latency and throughput) Expect to improve usability

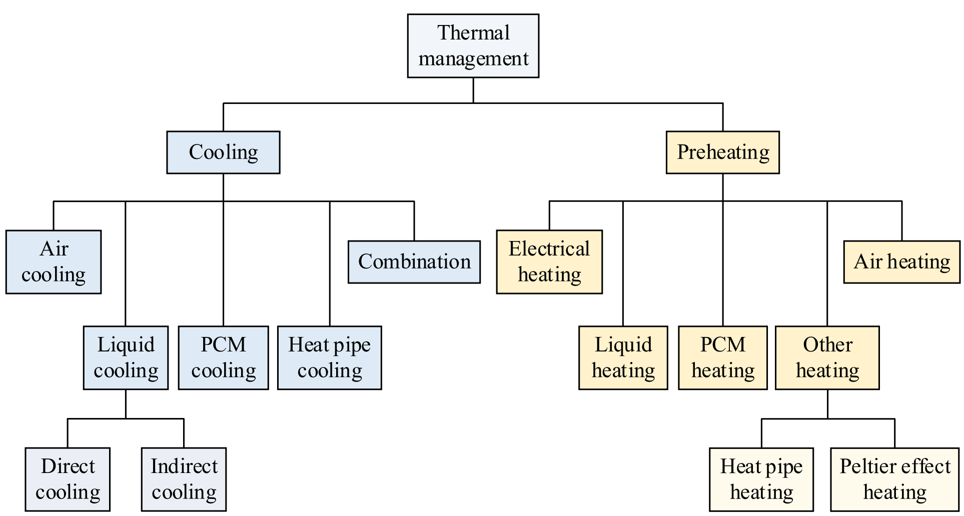

Fig. 20. Thermal management methods for electric vehicle batteries.

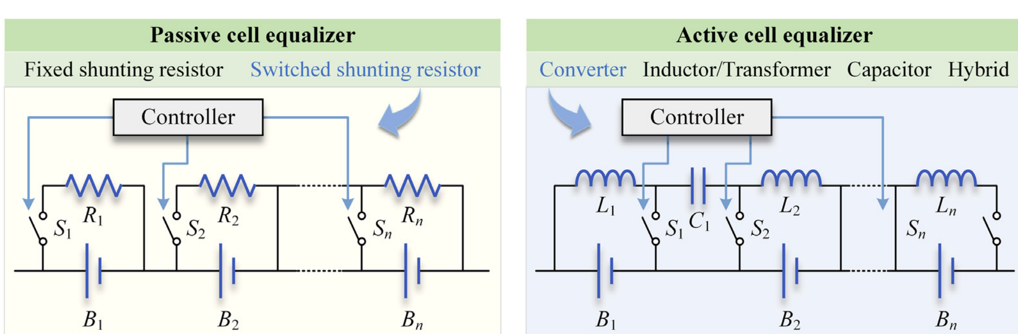

Fig. 21. Cell equalizers for voltage balancing in electric vehicle battery modules.

et al., 2013; Dai et al., 2021; Hu et al., 2020c). First, distributed fault diagnosis has been widely explored. The qualitative analysis methods were easy to interpret but not suitable for complex systems and over-reliant on knowledge integrity (Hu et al., 2020c).

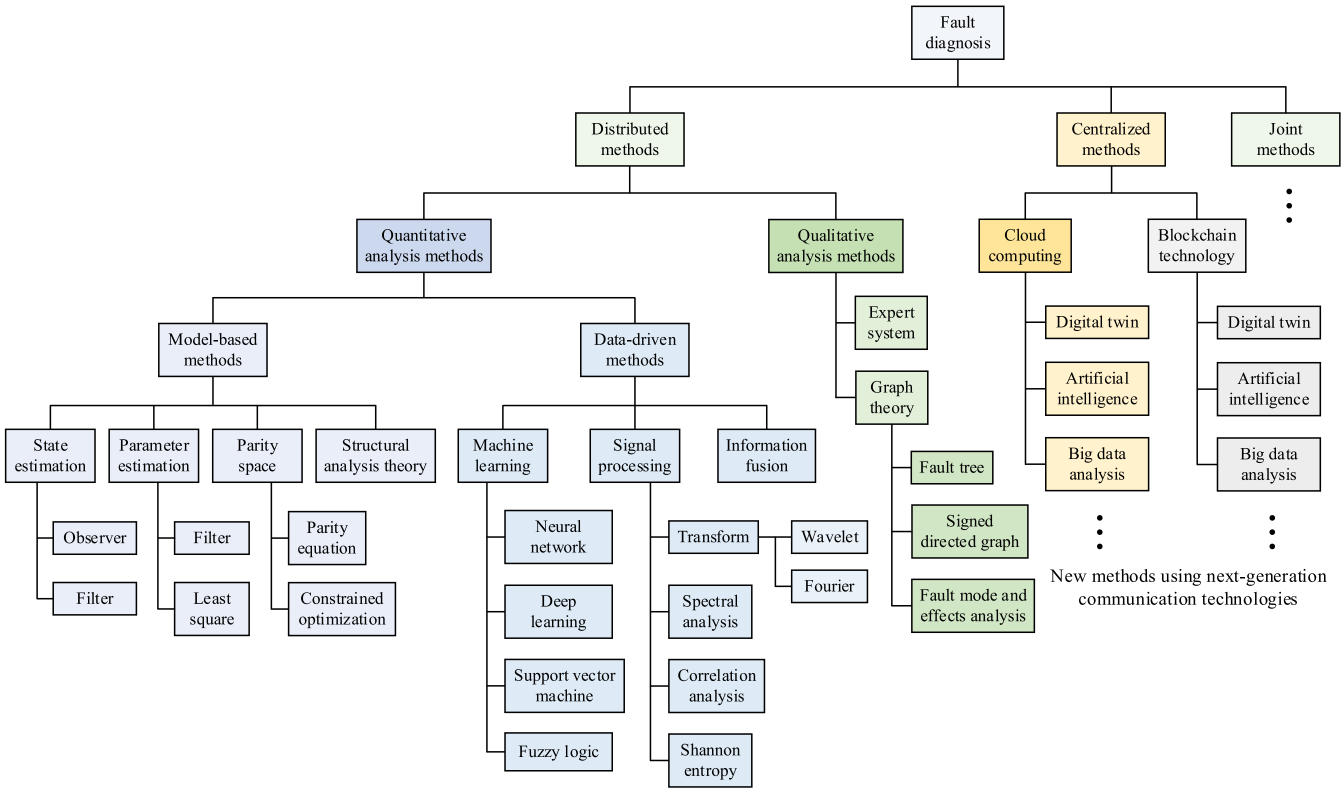

Fig. 22. Fault diagnosis methods for electric vehicle batteries.

Second, a model-based method was applied to diagnose the internal and external short-circuit faults with high accuracy (Xiong et al., 2020b; Feng et al., 2018). Based on an active model-based method, the reconfigurable battery systems were developed to improve the fault isolability (Schmid et al., 2021a). Third, data-driven methods comprise three approaches (Dai et al., 2021): (i) ML method, (ii) signal processing method, and (iii) information fusion method. For early fault prediction before thermal runaway, a novel data-driven method was reported with high sensitivity and robustness (Schmid et al., 2021b). A recurrent NN method was examined for the accurate fault diagnosis and precise locating of thermal runaway cells (Li et al., 2021g). Also, a multi-fault diagnosis method using the modified sample entropy was designed to detect early battery faults and prevent false detections (Shang et al., 2020). Next, the data-driven fault diagnosis will be still regarded as one of the most promising methods. Digital twin technology (Wu et al., 2020; Li et al., 2020b) is another alternative for online fault diagnosis to prevent catastrophic accidents. Besides, big data analysis (Zhao et al., 2017; Li and Zhao, 2021), data mining (Xiong et al., 2018a), and AI will try to establish a comprehensive fault diagnosis system for large-scale battery systems. Based on the cyber–physical platform, the CC technology may help solve the computational requirements of real-time fault diagnosis and provide an intelligent and cost-effective maintenance platform for regional battery networks (Kim et al., 2018).

4.3. Emerging management technologies

Nowadays, some emerging technologies advanced the BMSs for state estimation and prediction. These technologies mainly include multi-model co-estimation, AI, CC, and blockchain technology. They will benefit the batteries to fully exploit their potential performances and strengths.

4.3.1. Multi-model co-estimation

Developing high-fidelity battery models can improve the accuracy of state estimations, but it hits a bottleneck with the increase in complexity. In Fig. 23, a multi-model co-estimation method was put forward to combine the relative strengths of two or several approaches (Lin et al., 2017; Li et al., 2017; Wang, 2019). This method is promising to further improve precision and reliability. Accordingly, three ECMs and one genetic algorithm were joined to develop the concept of fusion estimation (Lin et al., 2017). To solve the coupling correlations, a multi-model probability fusion estimation was studied to realize the precise estimation (Li et al., 2017). Furthermore, several algorithms, such as support vector regression algorithm, linear regression algorithm, and random forest algorithm, were fused to support the SOC prediction (Wang, 2019). Besides, multi-state joint estimations also drew increasing attention. To estimate the SOC and SOT, an electrochemical-thermal NN was formulated with two submodels—a simplified single particle model and a lumped thermal model (Feng et al., 2020). For online multi-state estimation, a data-driven method, incorporating the least-square-support-vector-machine and model-based unscented-particle-filter, was studied with higher accuracy (Song et al., 2020). Another enhanced co-estimation hierarchy was devised to demonstrate the effectiveness and resilience of multi-state joint estimations, such as SOC, SOH, and SOP (Hu et al., 2020a).

4.3.2. Artificial intelligence

Thanks to the extensive spread of sensing equipment and the ever-increasing development of IoT devices, a wealth of data can be acquired more readily, and the digital embodiment of batteries will be dug deeper. Many data-driven AI methods, including the ML, support vector machines, radial basis functions, and recurrent NNs, have attracted more renewed attention (Vidal et al., 2020; Chandran et al., 2021; Xi et al., 2022). There remains a promising opportunity to merge the AI into a BMS

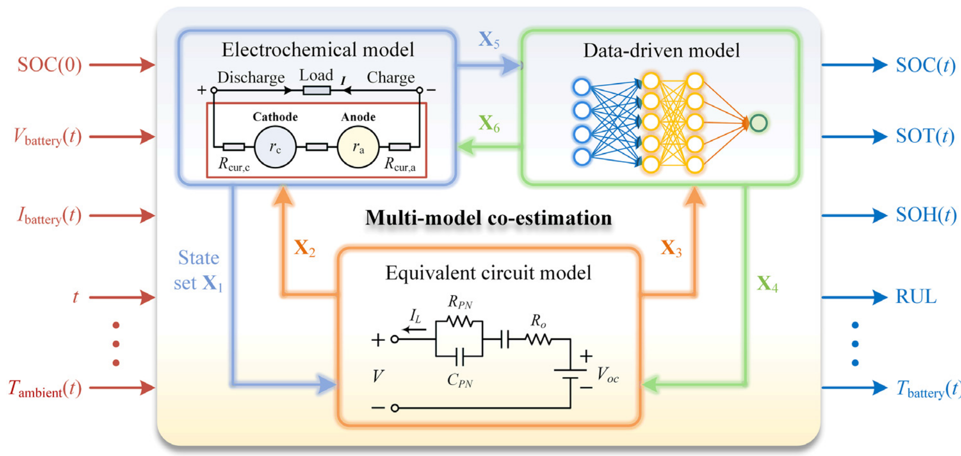

Fig. 23. Multi-model co-estimation for electric vehicle batteries.

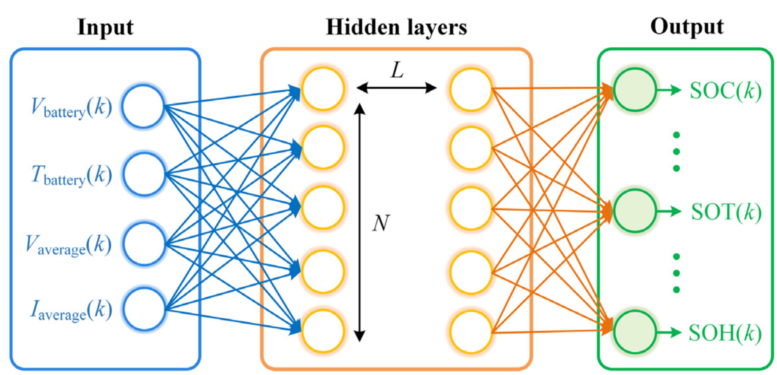

Fig. 24. Neural network model for battery state estimation.

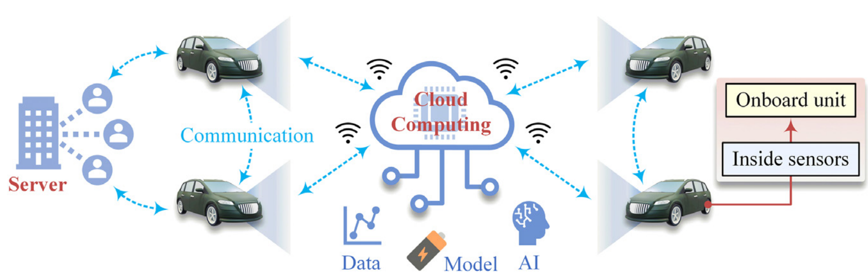

Fig. 25. Ecosystem of cloud computing and artificial intelligence for future electric vehicles.

towards creating a battery-information twin, which will offer an intelligent, accurate, and efficient framework for better estimating various battery states. Some research works have been rewarded with fruitful accomplishments. An artificial NN model was developed for predicting the LIBs' temperature (Jaliliantabar et al., 2022). Besides, a tuned genetic algorithm and an improved colliding body optimization were utilized to manage the battery SOC effectively (Som et al., 2020). Promisingly, a deep NN structure (Chemali et al., 2018) can be applied in the battery state estimation in Fig. 24. These AI-based tools will become a powerful enabler for future BMSs. The emerging fields will bring multidisciplinary challenges and expect technological breakthroughs around the security of data and information communication as well as the other relevant areas (Wu et al., 2020).

4.3.3. Cloud computing

The semiconductor industry and communication technology have both achieved unprecedented developments, especially such as the fifth-/sixth-generation and next-generation network technologies. The vehicular CC comes into being and mainly comprises three parts: (i) EVs, (ii) communication, and (iii) cloud framework (Hu et al., 2020b). A massive amount of real-time data will be gathered by a local server and uploaded onto the CC center to complete the complicated algorithms, such as data-driven AI, big data analysis, or data mining (Li and Zhao, 2021). Such algorithms are too time-consuming to handle the huge dataset by a local or onboard BMS. Fig. 25 shows an ecosystem of CC and AI for future EVs. By resource integration and data sharing, the cloud BMS built up the digital twin of battery systems and prognosed the SOH indicating the capacity fade and power fade due to aging (Li et al., 2020b). For real-time global optimization, a two-layer internet-distributed framework was exploited by using the CC technology and vehicular IoT (Zhang et al., 2020a). Besides SOH prognosis, fault diagnosis and state estimation can also be readily implemented by the CC platform and sent to the local

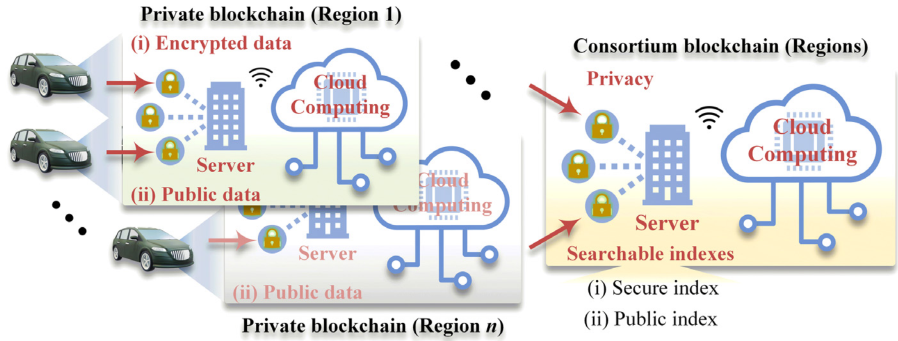

Fig. 26. Blockchain technology for battery management of electric vehicles.

BMS, thus realizing the remote diagnosis and maintenance service for a large-scale mobile EV energy network.

4.3.4. Blockchain technology

With vehicular data sharing among a league of several regions, blockchain technology adopts a two-layer hierarchy: (i) private blockchain, and (ii) consortium blockchain. In Fig. 26, the private blockchain records the original data including the encrypted and public ones of each user (EV), while the consortium blockchain collects the researchable indexes including the secure and public ones generated from the encrypted and public data, respectively (Hu et al., 2020b). Blockchain technology has the advantages of data security and integrity. It can protect the internet-connected BMSs from malicious cyber–physical attacks and enable intelligent monitoring, prognostic, and control (Kim et al., 2020) for a network of EVs. This technology was explored to collect the charging data from different stakeholders and outperformed the conventional algorithms by reducing the estimate errors of SOH (Jin et al., 2021). Besides the battery management in a regional league (Florea and Taralunga, 2020), blockchain technology can also support anonymous transactions with superior privacy.

5. Challenges and foresight

5.1. Batteries

From the perspective of automotive propulsion, two central challenges for high-energy batteries raise expectations on energy density, fast charging, and safety. To solve the challenges, the most promising batteries will be generated from the regimes of LIBs, LMBs, and technologies beyond lithium in the future.

5.1.1. Energy density, fast charging, and safety expectations

To promote carbon neutrality, the replacement of gasoline vehicles with EVs brings challenges for current battery technologies, especially in terms of energy density, fast charging, and safety. Both the swift launch and durable cruise are preferable for electric propulsions, but they highly depend on the energy density of batteries (Chau and Chan, 2007; Chau, 2016). Meanwhile, fast charging is also a major target in the automotive industry. The target is to charge by 3C or 4C to 80% capacity. Besides, the safety of EV batteries becomes more important than ever because it is closely related to personal and property safety, but the achievement of battery safety should be not at the expense of energy density (Pham et al., 2018). Many researchers are devoted to seeking technological breakthroughs by fully considering the rising expectations on energy density, fast charging, and safety (Sun et al., 2020b; Wu et al., 2019).

5.1.2. Battery technology trends

Promising candidates mainly fall into three streams: (i) LIBs, (ii) LMBs (especially SSBs), and (iii) alternative ion batteries (especially SIBs). First, LIBs will still dominate and promote the EV applications at least in the next decade(s). The lithium titanate-based technology can be considered as a possible alternative for developing fast-charging batteries with long cycle life for applications where energy density is not of major concern (e.g., electric buses). Second, more chemists and research institutes believe that Li-metal is the most promising anode material outweighing the others. Besides, many researchers recognized that Li–O_2 is a very challenging system and considered that many years of fundamental research are mandatory to bring this technology to practical applications (Placke et al., 2017). Third, alternative ion batteries will be continuously explored for developing new batteries. In particular, emerging SIBs exhibits competitive KPIs, and they may cooperate with LIBs for future EV propulsions.

A variety of chemistries regarding LIBs, LMBs (such as SSBs), and technologies beyond lithium (such as sodium/magnesium), rather than unique technology, will be developed as potential candidates (Duffner et al., 2021; Schmuch et al., 2018) to fulfill the specialized requirements for different industrial applications. These batteries' lifetime can reach at least 2000 cycles and >10 years which are acceptable for EV applications. Besides, V2V, V2H, and V2G operations will challenge the battery cycle life further. To enable instant energy trading in vehicular energy networks (Liu et al., 2022a; Nguyen, 2020), higher specific power will bring new challenges for EV energy storage systems.

5.2. Technologies regarding batteries

Battery management is also significant in helping batteries exert optimal KPIs in EV applications. For further advancing the battery management technologies, new technologies, including the sensor-on-chip, smart power electronics, and VIEI, will draw increasing attention.

5.2.1. New sensor-on-chip

No matter which model or method is chosen, state estimation, fault prognosis, and health diagnosis highly rely on various battery parameters. Hence, diverse sensors should be configured to sense the required parameters. Different sensors can be integrated onto one chip, termed sensor-on-chip. This new direction deserves to be explored for compacting the BMSs (Wang et al., 2014). Particularly, the on-chip thermal sensors (Che et al., 2010) can be mounted on the battery surface or deployed inside a battery, and they will form a wireless sensor network serving the surface and internal thermal management of batteries. We envision that the development of sensor-on-chip will contribute to a smarter BMS for EV batteries.

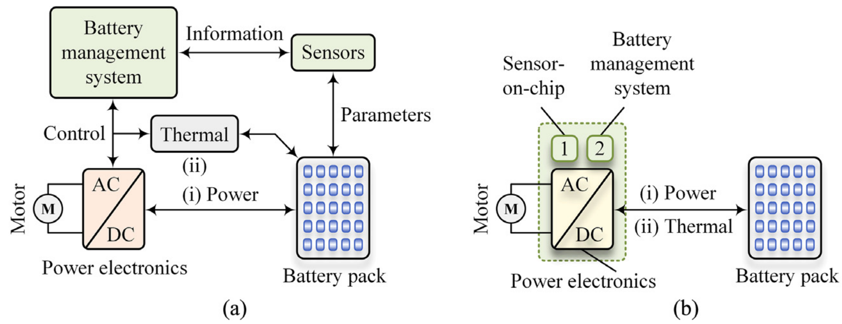

Fig. 27. Battery management and energy conversion system. (a) Separated power electronics and battery management. (b) Smart power electronics.

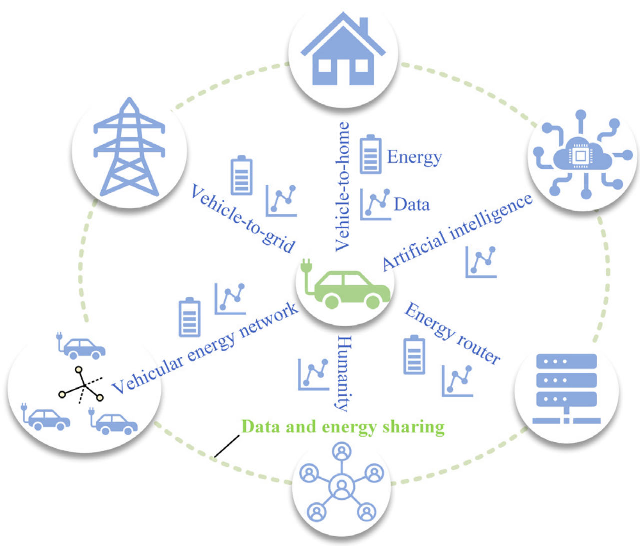

Fig. 28. Vehicular information and energy internet for data and energy sharing.

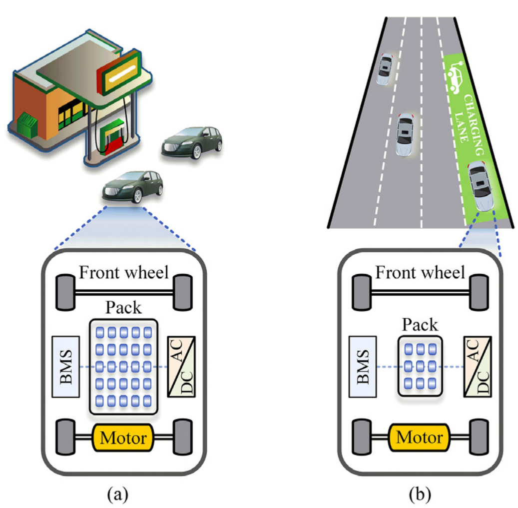

Fig. 29. Wireless charging. (a) Park-and-charge. (b) Move-and-charge.

5.2.2. Smart power electronics

A conventional energy conversion system is shown in Fig. 27(a). The power electronics and BMS are separated physically. For battery management, the BMS delivers control signals to power converters, and the conventional power electronics is in charge of charge/discharge management and motor drives (Cao et al., 2021; Li et al., 2021e,d). Thanks to the rapid developments of wide bandgap semiconductors (especially gallium nitride devices) and microcontrollers, power electronics will actively embrace the technologies of communication (He et al., 2020) and battery management in addition to power conversion in Fig. 27(b). Future power electronics will be capable of direct battery management with no independent BMS so that the software and hardware will be integrated as well. Typically, battery cell balancing and thermal management can be directly achieved by power converters only. Cooperating with the CC technology, smart power electronics can support the fault tolerance and health diagnosis and improve the reliability and intellectualization for managing the local EVs.

5.2.3. Vehicular information and energy internet

Information and energy exchange among EVs can alleviate the over-dependence on local batteries and BMSs. Such V2V operations can be readily extended to establish a vehicular energy network (Yi et al., 2014; Lam et al., 2017), and this EV network can be incorporated in a vehicular IoT that supports collaborative autonomous driving and advances the transportation systems (Peng et al., 2020). Wherein, the V2V, V2H, and V2G operations enable to share the private data and energy packets of EV batteries with energy routers. Fig. 28 envisions a VIEI for data and energy sharing. It can also promote the sharing of computing power among a wealth of EVs and the whole internet. With the help of AI and CC technologies, EVs will function far beyond transportation tools. Both EV batteries and their BMSs will evolve to embrace the information, energy, and humanity internet with new functions (Farman et al., 2020; Du et al., 2020). In the VIEI, the security and privacy of vehicular data and energy will bring new challenges for resisting malicious attackers. Hence, many researchers searched for potential methods to protect the security and privacy (Zhang et al., 2020b). Emerging technologies, such as blockchain technology, CC, and AI, will greatly promote a smarter VIEI.

5.3. Technologies replacing batteries

Advances in batteries and management technologies can straightforwardly address the concerns of energy and safety but still exhibit some lagging effects, especially in terms of the urgent requirements in the expanding EV market. Two alternative technologies, particularly wireless power drive, emerge to provide possible solutions to alleviate the urgency and even replace the high-energy batteries.

5.3.1. Move-and-charge

To mitigate the urgency of high energy capacity, wireless charging technologies can be regarded as an effective solution (Mi et al., 2016; Tian et al., 2021; Assawaworrarit and Fan, 2020). As the stationary and dynamic WPT, Fig. 29(a) and (b) show the

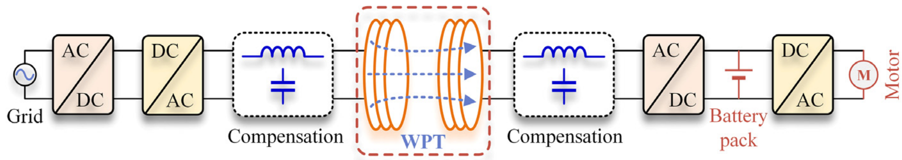

Fig. 30. Stationary/dynamic wireless charging for electric vehicle battery.

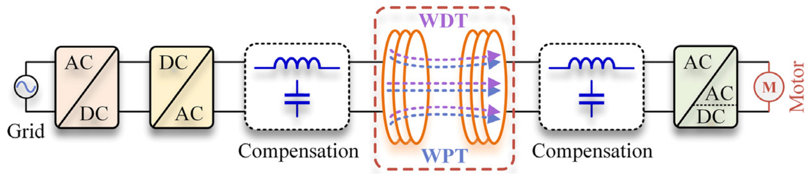

Fig. 31. Wireless power drive for electric vehicle mobility.

schematics of park-and-charge and move-and-charge (Lerosey, 2017), respectively. Each EV is allowable to be equipped with a small-size battery pack and can directly pick up wireless power from the charging lane when driving on the road. This move-and-charge technology offers the charging flexibility and convenience. In such scenarios, alike information encryption, wireless energy-on-demand (Liu et al., 2020b) and wireless energy encryption (Liu et al., 2020a) can be implemented to guarantee the energy security for wireless charging systems with multiple pick-ups. For EV charging, the harvest of renewable energy can be regarded as a second way to alleviate the demands of high-energy batteries.

5.3.2. Wireless power drive

A wireless charging topology is shown in Fig. 30, where the battery ought to get charged from the WPT system and then discharge its energy to drive the motor in the EV. However, the round-trip efficiency of EV battery packs is typically 70%∼80% for each charge-and-discharge cycle (Schimpe et al., 2018). Such a low efficiency is not preferable for high-efficiency energy utilization. To deal with this drawback, a promising technology of wireless motors was recognized as one of the best candidates to implement the new generation of EVs especially for harsh driving environments (Jiang et al., 2019a; Ludois et al., 2012). Furthermore, in Fig. 31, wireless power-and-drive transfer technology integrated WPT and wireless drive transfer (WDT) in only one channel (Liu et al., 2022b, 2021b). It directly utilizes the drive capability of wireless power and will surpass the scope of wireless motors by avoiding the use of batteries, controllers, and communication modules in receivers. This potential scheme can be further extended to a new application for various EV applications, termed wireless power drive.

5.4. Discussion and recommendation

With the ever-increasing demands of battery chemistry, battery technologies, such as LIBs, SSBs, and alternative-ion batteries, will be actively improved by global chemists, in particular, improving the energy density, fast charging, and safety concerns. These battery improvements will advance the EVs' performance. Sensor-on-chip and smart power electronics will play important roles in sensing and processing the information of energy and data. By embracing the advanced technologies of computers, servers, and AI methods, the vehicular information and energy internet will coordinatively handle the power flows and information flows among extensive EVs. Finally, wireless power transfer technologies, including move-and-charge and wireless power drive, can serve as potential solutions to get rid of the overdependence of high-energy batteries. The future EVs will evolve into BEVs and fuel cell EVs being equipped with high-energy batteries. Besides grounded EVs, electric ships and more electric aircraft will be fully developed in the future. The developed countries may move towards 100% EV transport at least by 2050.

6. Conclusions

To contribute a comprehensive and in-depth investigation, this article has thoroughly surveyed the state-of-the-art batteries and their management technologies for EV applications. Major features, pros and cons, new technological breakthroughs, and challenges and opportunities have been delineated in depth. The main contributions are summarized as follows:

(1) Both the roadmap and classification of EV batteries are elaborated clearly. Energy density, fast charging, and safety issues are identified as main concerns in the EV applications, and new foresight on EV batteries are newly presented, especially for the V2V and V2G operations in the wireless EV power network.
(2) Various methods of battery modeling, state estimation, and health diagnosis are comprehensively discussed. The data-driven state prediction can promisingly achieve an impressive accuracy of over 90.0% by using a dataset of the first 100 cycles only. Besides artificial intelligence, cloud computing, and blockchain technology, the new sensor-on-chip, smart power electronics, and vehicular information and energy internet are envisioned for smart and green mobility.
(3) The technologies replacing batteries, including move-and-charge and wireless power drive, are recommended as the potential solutions to alleviate the technical bottlenecks of developing EV batteries.

This critical review aims to propose a development blueprint for EV batteries, technologies regarding batteries, and technologies replacing batteries, especially considering the information and energy internet for data and energy sharing. Its main limitations are concerning the energy density, fast charging, and safety issues of LIBs as well as the real-time state prediction based on the practical dataset. Future direction is to develop the dynamic data-driven electrothermal model, which will be used for real-time state prediction, health diagnosis, and charging control.

CRediT authorship contribution statement

Wei Liu: Developed the idea, Carried out the analysis, Wrote this paper. **Tobias Placke:** Revised the whole paper, Made important suggestions. **K.T. Chau:** Developed the idea, Carried out the analysis, Wrote this paper.

Declaration of competing interest

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

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References

Akbarzadeh, M., Jaguemont, J., Kalogiannis, T., Karimi, D., He, J., Jin, L., et al., 2021. A novel liquid cooling plate concept for thermal management of lithium-ion batteries in electric vehicles. Energy Convers. Manage. 231, 113862.

Ali, M.U., Zafar, A., Nengroo, S.H., Hussain, S., Junaid Alvi, M., Kim, H.J., 2019. Towards a smarter battery management system for electric vehicle applications: A critical review of lithium-ion battery state of charge estimation. Energies 12, 446.

Alliance, G.B., 2019. A Vision for a Sustainable Battery Value Chain in 2030: Unlocking the Full Potential To Power Sustainable Development and Climate Change Mitigation. World Economic Forum, Geneva, Switzerland, pp. 1–52.

Assawaworrarit, S., Fan, S., 2020. Robust and efficient wireless power transfer using a switch-mode implementation of a nonlinear parity–time symmetric circuit. Nat Electron. 3, 273–279.

Attanayaka, A.M.S., Karunadasa, J.P., Hemapala, K.T., 2021. Comprehensive electro-thermal battery-model for Li-ion batteries in microgrid applications. Energy Storage 3, e230.

Bhargav, A., He, J., Gupta, A., Manthiram, A., 2020. Lithium-sulfur batteries: Attaining the critical metrics. Joule 4, 285–291.

Brandt, K., 1994. Historical development of secondary lithium batteries. Solid State Ion. 69, 173–183.

Bruce, P.G., Freunberger, S.A., Hardwick, L.J., Tarascon, J.M., 2012. Li-O_2 and Li-S batteries with high energy storage. Nature Mater. 11, 19–29.

Burke, A.F., 2007. Batteries and ultracapacitors for electric, hybrid, and fuel cell vehicles. Proc. IEEE 95, 806–820.

Cai, L., Meng, J., Stroe, D.-I., Peng, J., Luo, G., Teodorescu, R., 2020. Multiobjective optimization of data-driven model for lithium-ion battery SOH estimation with short-term feature. IEEE Trans. Power Electron. 35, 11855–11864.

Cao, L., Chau, K.T., Lee, C.H.T., Liu, W., Ching, T.W., 2021. Analysis of air-gap field modulation in parallel-hybrid-excited harmonic-shift machines. IEEE Trans. Magn. 57, 1–6.

2021. CATL sodium-ion battery official launch. Available online: https://www.youtube.com/watch?v=LxKtCquWx5c.

Chan, C.C., 2007. The state of the art of electric, hybrid, and fuel cell vehicles. Proc. IEEE 95, 704–718.

Chandran, V., Patil, C.K., Karthick, A., Ganeshaperumal, D., Rahim, R., Ghosh, A., 2021. State of charge estimation of lithium-ion battery for electric vehicles using machine learning algorithms. World Electr. Veh. J. 12, 38.

Chao, D., Zhou, W., Ye, C., Zhang, Q., Chen, Y., Gu, L., et al., 2019. An electrolytic Zn-MnO_2 battery for high-voltage and scalable energy storage. Angew. Chem. 131, 7905–7910.

Chau, K.T., 2016. Energy systems for electric and hybrid vehicles. Inst. Eng. Technol..

Chau, K.T., Chan, C.C., 2007. Emerging energy-efficient technologies for hybrid electric vehicles. Proc. IEEE 95, 821–835.

Chau, K.T., Wong, Y.S., 2002. Overview of power management in hybrid electric vehicles. Energy Convers. Manage. 43, 1953–1968.

Che, W., Meng, D., Chang, X., Chen, W., Wang, L., Yang, Y., et al., 2010. A semi-passive UHF RFID tag with on-chip temperature sensor. In: IEEE Custom Integrated Circuits Conference. pp. 1–4.

Chemali, E., Kollmeyer, P.J., Preindl, M., Emadi, A., 2018. State-of-charge estimation of li-ion batteries using deep neural networks: A machine learning approach. J. Power Sources 400, 242–255.

Chen, L., Fan, X., Ji, X., Chen, J., Hou, S., Wang, C., 2019a. High-energy li metal battery with lithiated host. Joule 3, 732–744.

Chen, Y., He, Y., Li, Z., Chen, L., Zhang, C., 2020a. Remaining useful life prediction and state of health diagnosis of lithium-ion battery based on second-order central difference particle filter. IEEE Access 8, 37305–37313.

Chen, S., Kuang, Q., Fan, H.J., 2020b. Dual-carbon batteries: Materials and mechanism. Small 16, 2002803.

Chen, H., Shen, Z., Pan, Z., Kou, Z., Liu, X., Zhang, H., et al., 2019b. Hierarchical micro-nano sheet arrays of nickel–cobalt double hydroxides for high-rate Ni–Zn batteries. Adv. Sci. 6, 1802002.

Chen, N., Zhang, P., Dai, J., Gui, W., 2020c. Estimating the state-of-charge of lithium-ion battery using an H-infinity observer based on electrochemical impedance model. IEEE Access 8, 26872–26884.

Choi, S.Y., Gu, B.W., Jeong, S.Y., Rim, C.T., 2015. Advances in wireless power transfer systems for roadway-powered electric vehicles. IEEE J. Emerg. Sel. Top. Power Electron. 3, 18–36.

Dai, H., Jiang, B., Hu, X., Lin, X., Wei, X., Pecht, M., 2021. Advanced battery management strategies for a sustainable energy future: Multilayer design concepts and research trends. Renew. Sustain. Energy Rev. 138, 110480.

Dai, H., Zhu, L., Zhu, J., Wei, X., Sun, Z., 2015. Adaptive Kalman filtering based internal temperature estimation with an equivalent electrical network thermal model for hard-cased batteries. J. Power Sources 293, 351–365.

Das, U.K., Shrivastava, P., Tey, K.S., Idris, M.Y.I.B., Mekhilef, S., Jamei, E., et al., 2020. Advancement of lithium-ion battery cells voltage equalization techniques: A review. Renew. Sustain. Energy Rev. 134, 110227.

Demir-Cakan, R., Palacin, M.R., Croguennec, L., 2019. Rechargeable aqueous electrolyte batteries: From univalent to multivalent cation chemistry. J. Mater. Chem. A 7, 20519–20539.

Deng, Z., Hu, X., Lin, X., Che, Y., Xu, L., Guo, W., 2020. Data-driven state of charge estimation for lithium-ion battery packs based on Gaussian process regression. Energy 205, 118000.

Deng, Z., Hu, X., Lin, X., Kim, Y., Li, J., 2021. Sensitivity analysis and joint estimation of parameters and states for all-solid-state batteries. IEEE Trans. Transp. Electrif. 7, 1314–1323.

Ding, X., Zhang, D., Cheng, J., Wang, B., Luk, P.C.K., 2019. An improved thevenin model of lithium-ion battery with high accuracy for electric vehicles. Appl. Energy 254, 113615.

Dong, G., Wei, J., Zhang, C., Chen, Z., 2016. Online state of charge estimation and open circuit voltage hysteresis modeling of $LiFePO_4$ battery using invariant imbedding method. Appl. Energy 162, 163–171.

Dong, G., Zhang, X., Zhang, C., Chen, Z., 2015. A method for state of energy estimation of lithium-ion batteries based on neural network model. Energy 90, 879–888.

Doughty, D.H., Roth, E.P., 2012. A general discussion of li ion battery safety. Electrochem. Soc. Interface 21, 37.

Doyle, M., Fuller, T.F., Newman, J., 1993. Modeling of galvanostatic charge and discharge of the lithium/polymer/insertion cell. J. Electrochem. Soc. 140, 1526.

Du, Z., Wu, C., Yoshinaga, T., Yau, K.L.A., Ji, Y., Li, J., 2020. Federated learning for vehicular internet of things: Recent advances and open issues. IEEE Open J. Comput. Soc. 1, 45–61.

Duan, B., Zhang, Q., Geng, F., Zhang, C., 2020. Remaining useful life prediction of lithium-ion battery based on extended Kalman particle filter. Int. J. Energy Res. 44, 1724–1734.

Duffner, F., Kronemeyer, N., Tübke, J., Leker, J., Winter, M., Schmuch, R., 2021. Post-lithium-ion battery cell production and its compatibility with lithium-ion cell production infrastructure. Nat. Energy 6, 123–134.

Dunn, B., Kamath, H., Tarascon, J.M., 2011. Electrical energy storage for the grid: A battery of choices. Science 334, 928–935.

Eichinger, G., Semrau, G., Lithiumbatterien, I., 1990a. Chemische grundlagen. Chem. Unserer Zeit 24, 32–36.

Eichinger, G., Semrau, G., Lithiumbatterien, I.I., 1990b. Entladereaktionen und komplette Zellen. Chem. Unserer Zeit 24, 90–96.

Farman, H., Jan, B., Khan, Z., Koubaa, A., 2020. A smart energy-based source location privacy preservation model for internet of things-based vehicular ad hoc networks. Trans. Emerg. Telecommun. Technol. 1–14.

Fei, Z., Yang, F., Tsui, K.-L., Li, L., Zhang, Z., 2021. Early prediction of battery lifetime via a machine learning based framework. Energy 225, 120205.

Feng, X., Pan, Y., He, X., Wang, L., Ouyang, M., 2018. Detecting the internal short circuit in large-format lithium-ion battery using model-based fault-diagnosis algorithm. J. Energy Storage 18, 26–39.

Feng, F., Teng, S., Liu, K., Xie, J., Xie, Y., Liu, B., et al., 2020. Co-estimation of lithium-ion battery state of charge and state of temperature based on a hybrid electrochemical-thermal-neural-network model. J. Power Sources 455, 227935.

Feng, X., Weng, C., He, X., Han, X., Lu, L., Ren, D., et al., 2019. Online state-of-health estimation for Li-ion battery using partial charging segment based on support vector machine. IEEE Trans. Veh. Technol. 68, 8583–8592.

Florea, B.C., Taralunga, D.D., 2020. Blockchain IoT for smart electric vehicles battery management. Sustainability 12, 3984.

Fotouhi, A., Auger, D.J., Propp, K., Longo, S., Wild, M., 2016. A review on electric vehicle battery modelling: From Lithium-ion toward Lithium–Sulphur. Renew. Sustain. Energy Rev. 56, 1008–1021.

Garche, J., Karden, E., Moseley, P.T., Rand, D.A, 2017. Lead–Acid Batteries for Future Automobiles. Elsevier.

Gong, X., Xiong, R., Mi, C.C., 2015. Study of the characteristics of battery packs in electric vehicles with parallel-connected lithium-ion battery cells. IEEE Trans. Ind. Appl. 51, 1872–1879.

Goodenough, J.B., 2018. How we made the li-ion rechargeable battery. Nat. Electron. 1, 204.
Goodenough, J.B., Park, K.S., 2013. The li-ion rechargeable battery: A perspective. J. Am. Chem. Soc. 135, 1167–1176.
Guo, Q., Zeng, W., Liu, S.L., Li, Y.Q., Xu, J.Y., Wang, J.X., et al., 2021. Recent developments on anode materials for magnesium-ion batteries: A review. Rare Met. 40, 290–308.
Han, X., Ouyang, M., Lu, L., Li, J., 2015. Simplification of physics-based electrochemical model for lithium ion battery on electric vehicle. Part II: Pseudo-two-dimensional model simplification and state of charge estimation. J. Power Sources 278, 814–825.
Han, W., Wik, T., Kersten, A., Dong, G., Zou, C., 2020. Next-generation battery management systems: Dynamic reconfiguration. IEEE Ind. Electron. Mag. 14, 20–31.
Hannan, M.A., Hoque, M.M., Hussain, A., Yusof, Y., Ker, P.J., 2018. State-of-the-art and energy management system of lithium-ion batteries in electric vehicle applications: Issues and recommendations. IEEE Access 6, 19362–19378.
Hannan, M.A., Lipu, M.S.H., Hussain, A., Mohamed, A., 2017. A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations. Renew. Sustain. Energy Rev. 78, 834–854.
Hariprakash, B., Shukla, A.K., 2009. Secondary Batteries—Nickel Systems | Nickel-Metal Hydride: Overview. In: Encyclopedia of Electrochemical Power Sources, Elsevier, pp. 494–501.
He, X., Wang, R., Wu, J., Li, W., 2020. Nature of power electronics and integration of power conversion with communication for talkative power. Nature Commun. 11, 2479.
How, D.N., Hannan, M.A., Lipu, M.S.H., Sahari, K.S., Ker, P.J., Muttaqi, K.M., 2020. State-of-charge estimation of Li-ion battery in electric vehicles: A deep neural network approach. IEEE Trans. Ind. Appl. 56, 5565–5574.
Hu, X., Jiang, H., Feng, F., Liu, B., 2020a. An enhanced multi-state estimation hierarchy for advanced lithium-ion battery management. Appl. Energy 257, 114019.
Hu, X., Li, S., Peng, H., 2012. A comparative study of equivalent circuit models for li-ion batteries. J. Power Sources 198, 359–367.
Hu, X., Liu, W., Lin, X., Xie, Y., Foley, A.M., Hu, L., 2021. A control-oriented electrothermal model for pouch-type electric vehicle batteries. IEEE Trans. Power Electron. 36, 5530–5544.
Hu, X., Xu, L., Lin, X., Pecht, M., 2020b. Battery lifetime prognostics. Joule 4, 310–346.
Hu, P., Yan, M., Zhu, T., Wang, X., Wei, X., Li, J., et al., 2017. Zn/V_2O_5 aqueous hybrid-ion battery with high voltage platform and long cycle life. ACS Appl. Mater. Interfaces 9, 42717–42722.
Hu, X., Zhang, K., Liu, K., Lin, X., Dey, S., Onori, S., 2020c. Advanced fault diagnosis for lithium-ion battery systems: A review of fault mechanisms, fault features, and diagnosis procedures. IEEE Ind. Electron. Mag. 14, 65–91.
Huang, L., Li, J., Liu, B., Li, Y., Shen, S., Deng, S., et al., 2020a. Electrode design for lithium–sulfur batteries: Problems and solutions. Adv. Funct. Mater. 30, 1910375.
Huang, G., Wang, J., Zhang, X., 2020b. Electrode protection in high-efficiency Li-O_2 batteries. ACS Cent. Sci. 6, 2136–2148.
Hwang, J.Y., Myung, S.T., Sun, Y.K., 2017. Sodium-ion batteries: Present and future. Chem. Soc. Rev. 46, 3529–3614.
İnci, M., Büyük, M., Demir, M.H., İlbey, G., 2021. A review and research on fuel cell electric vehicles: Topologies, power electronic converters, energy management methods, technical challenges, marketing and future aspects. Renew. Sustain. Energy Rev. 137, 110648.
Infante, W., Ma, J., Han, X., Liebman, A., 2020. Optimal recourse strategy for battery swapping stations considering electric vehicle uncertainty. IEEE Trans. Intell. Transp. Syst. 21, 1369–1379.
Jaliliantabar, F., Mamat, R., Kumarasamy, S., 2022. Prediction of lithium-ion battery temperature in different operating conditions equipped with passive battery thermal management system by artificial neural networks. Mater. Today: Proc. 48, 1796–1804.
Janek, J., Zeier, W.G., 2016. A solid future for battery development. Nat. Energy 1, 16141.
Jiang, C., Chau, K.T., Liu, C., Lee, C.H.T., Han, W., Liu, W., 2018. Move-and-charge system for automatic guided vehicles. IEEE Trans. Magn. 54, 1–5.
Jiang, C., Chau, K.T., Liu, W., Liu, C., Han, W., Lam, W.H., 2019a. An LCC compensated multiple-frequency wireless motor system. IEEE Trans. Ind. Inform. 15, 6023–6034.
Jiang, X., Luo, L., Zhong, F., Feng, X., Chen, W., Ai, X., et al., 2019b. Electrolytes for dual-carbon batteries. ChemElectroChem 6, 2615–2629.
Jiang, C., Wang, S., Wu, B., Fernandez, C., Xiong, X., Coffie-Ken, J., 2021. A state-of-charge estimation method of the power lithium-ion battery in complex conditions based on adaptive square root extended Kalman filter. Energy 219, 119603.
Jilte, R., Afzal, A., Panchal, S., 2021. A novel battery thermal management system using nano-enhanced phase change materials. Energy 219, 119564.
Jin, R., Wei, B., Luo, Y., Ren, T., Wu, R., 2021. Blockchain-based data collection with efficient anomaly detection for estimating battery state-of-health. IEEE Sens. J. 21, 13455–13465.
Johnson, V., 2002. Battery performance models in ADVISOR. J. Power Sources 110, 321–329.
Johnson, I.D., Ingram, B.J., Cabana, J., 2021. The quest for functional oxide cathodes for magnesium batteries: a critical perspective. ACS Energy Lett. 6, 1892–1900.
Kim, J., Chun, H., Kim, M., Han, S., Lee, J.W., Lee, T.K., 2021. Effective and practical parameters of electrochemical Li-ion battery models for degradation diagnosis. J. Energy Storage 42, 103077.
Kim, T., Makwana, D., Adhikaree, A., Vagdoda, J.S., Lee, Y., 2018. Cloud-based battery condition monitoring and fault diagnosis platform for large-scale lithium-ion battery energy storage systems. Energies 11, 125.
Kim, T., Ochoa, J., Faika, T., Mantooth, A., Di, J., Li, Q., et al., 2020. An overview of cyber–physical security of battery management systems and adoption of blockchain technology. IEEE J. Emerg. Sel. Top. Power Electron. http://dx.doi.org/10.1109/JESTPE.2020.2968490.
Kleiner, J., Stuckenberger, M., Komsiyska, L., Endisch, C., 2021. Advanced monitoring and prediction of the thermal state of intelligent battery cells in electric vehicles by physics-based and data-driven modeling. Batteries 7.
Klintberg, A., Zou, C., Fridholm, B., Wik, T., 2019. Kalman filter for adaptive learning of two-dimensional look-up tables applied to OCV-curves for aged battery cells. Control Eng. Pract. 84, 230–237.
Konarov, A., Voronina, N., Jo, J.H., Bakenov, Z., Sun, Y.K., Myung, S.T., 2018. Present and future perspective on electrode materials for rechargeable zinc-ion batteries. ACS Energy Lett. 3, 2620–2640.
Laadjal, K., Cardoso, AJM., 2021. Estimation of lithium-ion batteries state-condition in electric vehicle applications: Issues and state of the art. Electronics 10, 1588.
Lam, A.Y.S., Leung, K., Li, V.O.K., 2017. Vehicular energy network. IEEE Trans. Transp. Electrif. 3, 392–404.
Lee, Y.-G., Fujiki, S., Jung, C., Suzuki, N., Yashiro, N., Omoda, R., et al., 2020. High-energy long-cycling all-solid-state lithium metal batteries enabled by silver–carbon composite anodes. Nat. Energy 5, 299–308.
Lee, C.Y., Lee, S.J., Hung, Y.M., Hsieh, C.T., Chang, Y.M., Huang, Y.T., et al., 2017. Integrated microsensor for real-time microscopic monitoring of local temperature, voltage and current inside lithium ion battery. Sensors Actuator A 253, 59–68.
Lerosey, G., 2017. Wireless power on the move. Nature 546, 354–355.
Lewis, G.N., Keyes, F.G., 1912. The potential of the potassium electrode. J. Am. Chem. Soc. 34, 119–122.
Lewis, G.N., Keyes, F.G., 1913. The potential of the lithium electrode. J. Am. Chem. Soc. 35, 340–344.
Li, C., Cui, N., Wang, C., Zhang, C., 2021a. Reduced-order electrochemical model for lithium-ion battery with domain decomposition and polynomial approximation methods. Energy 221.
Li, W., Erickson, E.M., Manthiram, A., 2020a. High-nickel layered oxide cathodes for lithium-based automotive batteries. Nat. Energy 5, 26–34.
Li, S., Fang, H., Shi, B., 2021b. Remaining useful life estimation of lithium-ion battery based on interacting multiple model particle filter and support vector regression. Reliab. Eng. Syst. Saf. 210, 107542.
Li, Y., Li, K., Liu, X., Wang, Y., Zhang, L., 2021c. Lithium-ion battery capacity estimation – A pruned convolutional neural network approach assisted with transfer learning. Appl. Energy 285, 116410.
Li, Y., Liu, K., Foley, A.M., Zülke, A., Berecibar, M., Nanini-Maury, E., et al., 2019. Data-driven health estimation and lifetime prediction of lithium-ion batteries: A review. Renew. Sustain. Energy Rev. 113, 109254.
Li, G., Lu, X., Kim, J.Y., Meinhardt, K.D., Chang, H.J., Canfield, N.L., et al., 2016. Advanced intermediate temperature sodium–nickel chloride batteries with ultra-high energy density. Nature Commun. 7, 1–6.
Li, Z., Mu, X., Zhao-Karger, Z., Diemant, T., Behm, R.J., Kübel, C., et al., 2018. Fast kinetics of multivalent intercalation chemistry enabled by solvated magnesium-ions into self-established metallic layered materials. Nature Commun. 9, 5115.
Li, W., Rentemeister, M., Badeda, J., Jöst, D., Schulte, D., Sauer, D.U., 2020b. Digital twin for battery systems: Cloud battery management system with online state-of-charge and state-of-health estimation. J. Energy Storage 30, 101557.
Li, Y., Wang, C., Gong, J., 2017. A multi-model probability SOC fusion estimation approach using an improved adaptive unscented Kalman filter technique. Energy 141, 1402–1415.
Li, X., Xue, Z., Yan, X., Zhang, L., Ma, W., Hua, W., 2021d. Low-complexity multivector-based model predictive torque control for PMSM with voltage preselection. IEEE Trans. Power Electron. 36, 11726–11738.
Li, X., Xue, Z., Zhang, L., Hua, W., 2021e. A low-complexity three-vector-based model predictive torque control for SPMSM. IEEE Trans. Power Electron. 36, 13002–13012.
Li, D., Yang, L., Li, C., 2021f. Control-oriented thermal-electrochemical modeling and validation of large size prismatic lithium battery for commercial applications. Energy 214, 119057.

Li, D., Zhang, Z., Liu, P., Wang, Z., Zhang, L., 2021g. Battery fault diagnosis for electric vehicles based on voltage abnormality by combining the long short-term memory neural network and the equivalent circuit model. IEEE Trans. Power Electron. 36, 1303–1315.

Li, S., Zhao, P., 2021. Big data driven vehicle battery management method: A novel cyber–physical system perspective. J. Energy Storage 33, 102064.

Lin, K., Chen, Y., Liu, Y., Zhang, B., 2020. Reliability prediction of battery management system for electric vehicles based on accelerated degradation test: A semi-parametric approach. IEEE Trans. Veh. Technol. 69, 12694–12704.

Lin, C., Mu, H., Xiong, R., Cao, J., 2017. Multi-model probabilities based state fusion estimation method of lithium-ion battery for electric vehicles: State-of-energy. Appl. Energy 194, 560–568.

Lindgren, J., Asghar, I., Lund, P.D., 2016. A hybrid lithium-ion battery model for system-level analyses. Int. J. Energy Res. 40, 1576–1592.

Ling, L., Wei, Y., 2021. State-of-charge and state-of-health estimation for lithium-ion batteries based on dual fractional-order extended Kalman filter and online parameter identification. IEEE Access 9, 47588–47602.

Liu, W., Chau, K.T., Chow, C.C.T., Lee, C.H.T., 2022a. Wireless energy trading in traffic internet. IEEE Trans. Power Electron. 37, 4831–4841.

Liu, W., Chau, K.T., Hua, Z., 2021a. Overview of batteries for electric vehicle propulsion. In: Proceeding of 34th International Electric Vehicle Symposium & Exhibition. Nanjing, China. pp. 1–12.

Liu, W., Chau, K.T., Lee, C.H.T., Cao, L., Han, W., 2022b. Wireless power and drive transfer for piping network. IEEE Trans. Ind. Electron. 69, 2345–2356.

Liu, W., Chau, K.T., Lee, C.H.T., Cao, L., Jiang, C., 2021b. Frequency-modulated wireless direct-drive motor control. IEEE Trans. Magn. 57, 1–7.

Liu, W., Chau, K.T., Lee, C.H.T., Han, W., Tian, X., Lam, W.H., 2020a. Full-range soft-switching pulse frequency modulated wireless power transfer. IEEE Trans. Power Electron. 35, 6533–6547.

Liu, W., Chau, K., Lee, C.H., Jiang, C., Han, W., 2018. A switched-capacitorless energy-encrypted transmitter for roadway-charging electric vehicles. IEEE Trans. Magn. 54, 1–6.

Liu, W., Chau, K.T., Lee, C.H.T., Jiang, C., Han, W., Lam, W.H., 2020b. Wireless energy-on-demand using magnetic quasi-resonant coupling. IEEE Trans. Power Electron. 35, 9057–9069.

Liu, C., Chau, K.T., Lee, C.H.T., Song, Z., 2021c. A critical review of advanced electric machines and control strategies for electric vehicles. Proc. IEEE 109, 1004–1028.

Liu, C., Chau, K.T., Wu, D., Gao, S., 2013. Opportunities and challenges of vehicle-to-home, vehicle-to-vehicle, and vehicle-to-grid technologies. Proc. IEEE 101, 2409–2427.

Liu, C., Hu, M., Jin, G., Xu, Y., Zhai, J., 2021d. State of power estimation of lithium-ion battery based on fractional-order equivalent circuit model. J. Energy Storage 41, 102954.

Liu, K., Li, K., Peng, Q., Zhang, C., 2019. A brief review on key technologies in the battery management system of electric vehicles. Front. Mech. Eng. 14, 47–64.

Liu, Y., Ma, R., Pang, S., Xu, L., Zhao, D., Wei, J., et al., 2021e. A nonlinear observer SOC estimation method based on electrochemical model for lithium-ion battery. IEEE Trans. Ind. Appl. 57, 1094–1104.

Liu, T., Tan, W., Tang, X., Zhang, J., Xing, Y., Cao, D., 2021f. Driving conditions-driven energy management strategies for hybrid electric vehicles: A review. Renew. Sustain. Energy Rev. 151, 111521.

Lu, L., Han, X., Li, J., Hua, J., Ouyang, M., 2013. A review on the key issues for lithium-ion battery management in electric vehicles. J. Power Sources 226, 272–288.

Ludois, D.C., Reed, J.K., Hanson, K., 2012. Capacitive power transfer for rotor field current in synchronous machines. IEEE Trans. Power Electron. 27, 4638–4645.

Lukic, S.M., Cao, J., Bansal, R.C., Rodriguez, F., Emadi, A., 2008. Energy storage systems for automotive applications. IEEE Trans. Ind. Electron. 55, 2258–2267.

Ma, L., Li, L., Liu, Y., Zhu, J., Meng, T., Zhang, H., et al., 2018. Building better rechargeable Zn-Mn batteries with a highly active Mn_3O_4/carbon nanowire cathode and neutral Na_2SO_4/$MnSO_4$ electrolyte. Chem. Commun. 54, 10835–10838.

Mc Carthy, K., Gullapalli, H., Ryan, K.M., Kennedy, T., 2021. Use of impedance spectroscopy for the estimation of Li-ion battery state of charge, state of health and internal temperature. J. Electrochem. Soc. 168, 080517.

Mi, C.C., Buja, G., Choi, S.Y., Rim, C.T., 2016. Modern advances in wireless power transfer systems for roadway powered electric vehicles. IEEE Trans. Ind. Electron. 63, 6533–6545.

Miguel, E., Plett, G.L., Trimboli, M.S., Lopetegi, I., Oca, L., Iraola, U., et al., 2021. Electrochemical model and sigma point Kalman filter based online oriented battery model. IEEE Access 9, 98072–98090.

Mizushima, K., Jones, P., Wiseman, P., Goodenough, J.B., 1980. Li_xCoO_2 ($0<x<-1$): A new cathode material for batteries of high energy density. Mater. Res. Bull. 15, 783–789.

Mohammed, S.A.Q., Jung, J.W., 2021. A comprehensive state-of-the-art review of wired/wireless charging technologies for battery electric vehicles: Classification/common topologies/future research issues. IEEE Access 9, 19572–19585.

Nemeth, T., Schröer, P., Kuipers, M., Sauer, D.U., 2020. Lithium titanate oxide battery cells for high-power automotive applications – Electro-thermal properties, aging behavior and cost considerations. J. Energy Storage 31, 101656.

Ng, M.-F., Zhao, J., Yan, Q., Conduit, G.J., Seh, Z.W., 2020. Predicting the state of charge and health of batteries using data-driven machine learning. Nat. Mach. Intell. 2, 161–170.

Nguyen, D.H., 2020. Electric vehicle – Wireless charging-discharging lane decentralized peer-to-peer energy trading. IEEE Access 8, 179616-17925.

Omariba, Z.B., Zhang, L., Sun, D., 2019. Review of battery cell balancing methodologies for optimizing battery pack performance in electric vehicles. IEEE Access 7, 129335-129352.

Ouyang, Q., Chen, J., Zheng, J., Fang, H., 2018a. Optimal cell-to-cell balancing topology design for serially connected lithium-ion battery packs. IEEE Trans. Sustain. Energy 9, 350–360.

Ouyang, Q., Chen, J., Zheng, J., Hong, Y., 2018b. SOC estimation-based quasi-sliding mode control for cell balancing in lithium-ion battery packs. IEEE Trans. Ind. Electron. 65, 3427–3436.

Ouyang, Q., Han, W., Zou, C., Xu, G., Wang, Z., 2019. Cell balancing control for lithium-ion battery packs: A hierarchical optimal approach. IEEE Trans. Ind. Inform. 16, 5065–5075.

Pang, H., Guo, L., Wu, L., Jin, J., Zhang, F., Liu, K., 2021. A novel extended Kalman filter-based battery internal and surface temperature estimation based on an improved electro-thermal model. J. Energy Storage 41, 102854.

Peng, C., Wu, C., Gao, L., Zhang, J., Alvin Yau, K.L., Ji, Y., 2020. Blockchain for vehicular internet of things: Recent advances and open issues. Sensors 20, 5079.

Pham, H.Q., Lee, H.Y., Hwang, E.H., Kwon, Y.G., Song, S.W., 2018. Non-flammable organic liquid electrolyte for high-safety and high-energy density Li-ion batteries. J. Power Sources 404, 13–19.

Placke, T., Heckmann, A., Schmuch, R., Meister, P., Beltrop, K., Winter, M., 2018. Perspective on performance, cost, and technical challenges for practical dual-ion batteries. Joule 2, 2528–2550.

Placke, T., Kloepsch, R., Dühnen, S., Winter, M., 2017. Lithium ion, lithium metal, and alternative rechargeable battery technologies: The odyssey for high energy density. J. Solid State Electrochem. 21, 1939–1964.

Pozzi, A., Ciaramella, G., Volkwein, S., Raimondo, D.M., 2019. Optimal design of experiments for a lithium-ion cell: Parameters identification of an isothermal single particle model with electrolyte dynamics. Ind. Eng. Chem. Res. 58, 1286–1299.

Raijmakers, L., Danilov, D., Eichel, R.A., Notten, P., 2019. A review on various temperature-indication methods for li-ion batteries. Appl. Energy 240, 918–945.

Rand, D.A.J., PTM, 2009. Secondary Batteries—Lead–Acid Systems | Overview. Elsevier.

Rao, Z., Wang, S., 2011. A review of power battery thermal energy management. Renew. Sustain. Energy Rev. 15, 4554–4571.

Ren, X., Liu, S., Yu, X., Dong, X., 2021. A method for state-of-charge estimation of lithium-ion batteries based on PSO-LSTM. Energy 121236.

Robillard, C., 2005. Lithium-metal-polymer batteries. In: IEEE Power Engineering Society General Meeting. pp. 1223–1227.

Roman, D., Saxena, S., Robu, V., Pecht, M., Flynn, D., 2021. Machine learning pipeline for battery state-of-health estimation. Nat. Mach. Intell. 3, 447–456.

Romero-Becerril, A., Alvarez-Icaza, L., 2011. Comparison of discretization methods applied to the single-particle model of lithium-ion batteries. J. Power Sources 196, 10267–10279.

Ruan, H., Sun, B., Jiang, J., Zhang, W., He, X., Su, X., et al., 2021. A modified-electrochemical impedance spectroscopy-based multi-time-scale fractional-order model for lithium-ion batteries. Electrochim. Acta 394, 139066.

Sanguesa, J.A., Torres-Sanz, V., Garrido, P., Martinez, F.J., Marquez-Barja, J.M., 2021. A review on electric vehicles: Technologies and challenges. Smart Cities 4, 372–404.

Schimpe, M., Naumann, M., Truong, N., Hesse, H.C., Santhanagopalan, S., Saxon, A., et al., 2018. Energy efficiency evaluation of a stationary lithium-ion battery container storage system via electro-thermal modeling and detailed component analysis. Appl. Energy 210, 211–229.

Schmid, M., Gebauer, E., Hanzl, C., Endisch, C., 2021a. Active model-based fault diagnosis in reconfigurable battery systems. IEEE Trans. Power Electron. 36, 2584–2597.

Schmid, M., Kneidinger, H.G., Endisch, C., 2021b. Data-driven fault diagnosis in battery systems through cross-cell monitoring. IEEE Sens. J. 21, 1829–1837.

Schmuch, R., Wagner, R., Hörpel, G., Placke, T., Winter, M., 2018. Performance and cost of materials for lithium-based rechargeable automotive batteries. Nat. Energy 3, 267–278.

Senthil, C., Park, J.W., Shaji, N., Sim, G.S., Lee, C.W., 2022. Biomass seaweed-derived nitrogen self-doped porous carbon anodes for sodium-ion batteries: Insights into the structure and electrochemical activity. J. Energy Chem. 64, 286–295.
Severson, K.A., Attia, P.M., Jin, N., Perkins, N., Jiang, B., Yang, Z., et al., 2019. Data-driven prediction of battery cycle life before capacity degradation. Nat. Energy 4, 383–391.
Shang, Y., Lu, G., Kang, Y., Zhou, Z., Duan, B., Zhang, C., 2020. A multi-fault diagnosis method based on modified Sample Entropy for lithium-ion battery strings. J. Power Sources 446, 227275.
Shen, J., Dusmez, S., Khaligh, A., 2014. Optimization of sizing and battery cycle life in battery/ultracapacitor hybrid energy storage systems for electric vehicle applications. IEEE Trans. Ind. Inform. 10, 2112–2121.
Shen, S., Sadoughi, M., Li, M., Wang, Z., Hu, C., 2020. Deep convolutional neural networks with ensemble learning and transfer learning for capacity estimation of lithium-ion batteries. Appl. Energy 260, 114296.
Shen, Y., Zhang, Q., Wang, Y., Gu, L., Zhao, X., Shen, X., 2021. A pyrite iron disulfide cathode with a copper current collector for high-energy reversible magnesium-ion storage. Adv. Mater. 33, 2103881.
Singirikonda, S., Obulesu, Y., 2021. Active cell voltage balancing of electric vehicle batteries by using an optimized switched capacitor strategy. J. Energy Storage 38, 102521.
Slater, M.D., Kim, D., Lee, E., Johnson, C.S., 2013. Sodium-ion batteries. Adv. Funct. Mater. 23, 947–958.
Som, T., Dwivedi, M., Dubey, C., Sharma, A., 2020. Parametric studies on artificial intelligence techniques for battery SOC management and optimization of renewable power. Procedia Comput. Sci. 167, 353–362.
Song, Y., Liu, D., Liao, H., Peng, Y., 2020. A hybrid statistical data-driven method for on-line joint state estimation of lithium-ion batteries. Appl. Energy 261, 114408.
Song, Y., Peng, Y., Liu, D., 2021. Model-based health diagnosis for lithium-ion battery pack in space applications. IEEE Trans. Ind. Electron. 68, 12375–12384.
Song, M., Tan, H., Chao, D., Fan, H.J., 2018. Recent advances in Zn-ion batteries. Adv. Funct. Mater. 28, 1802564.
Sudworth, J., 2001. The sodium/nickel chloride (ZEBRA) battery. J. Power Sources 100, 149–163.
Sun, L., Li, G., You, F., 2020a. Combined internal resistance and state-of-charge estimation of lithium-ion battery based on extended state observer. Renew. Sustain. Energy Rev. 131, 109994.
Sun, W., Wang, F., Zhang, B., Zhang, M., Küpers, V., Ji, X., et al., 2021a. A rechargeable zinc-air battery based on zinc peroxide chemistry. Science 371, 46–51.
Sun, D., Yu, X., Wang, C., Zhang, C., Huang, R., Zhou, Q., et al., 2021b. State of charge estimation for lithium-ion battery based on an Intelligent Adaptive Extended Kalman Filter with improved noise estimator. Energy 214, 119025.
Sun, H., Zhu, G., Zhu, Y., Lin, M.C., Chen, H., Li, Y.Y., et al., 2020b. High-safety and high-energy-density lithium metal batteries in a novel ionic-liquid electrolyte. Adv. Mater. 32, 2001741.
Tamilselvi, S., Gunasundari, S., Karuppiah, N., Razak, R.K.A., Madhusudan, S., Nagarajan, V.M., et al., 2021. A review on battery modelling techniques. Sustainability 13, 10042.
Tan, W.K., Kawamura, G., Muto, H., Matsuda, A., 2021. Current progress in the development of fe-air batteries and their prospects for next-generation batteries. In: Sustainable Materials for Next Generation Energy Devices. Elsevier, pp. 59–83.
Tang, X., Liu, K., Wang, X., Gao, F., Macro, J., Widanage, W.D., 2020. Model migration neural network for predicting battery aging trajectories. IEEE Trans. Transp. Electrif. 6, 363–374.
Tang, X., Liu, K., Wang, X., Liu, B., Gao, F., Widanage, W.D., 2019. Real-time aging trajectory prediction using a base model-oriented gradient-correction particle filter for lithium-ion batteries. J. Power Sources 440, 227118.
Tarascon, J., Armand, M., 2011. Issues and challenges facing rechargeable lithium batteries. Nature 414, 359–367.
Thackeray, M.M., Wolverton, C., Isaacs, E.D., 2012. Electrical energy storage for transportation—approaching the limits of, and going beyond, lithium-ion batteries. Energy Environ. Sci. 5, 7854–7863.
Thangavel, V., Guerrero, O.X., Quiroga, M., Mikala, A.M., Rucci, A., Franco, A.A., 2020. A three dimensional kinetic Monte Carlo model for simulating the carbon/sulfur mesostructural evolutions of discharging lithium sulfur batteries. Energy Storage Mater. 24, 472–485.
Tian, X., Chau, K.T., Liu, W., Lee, CHT., 2021. Selective wireless power transfer using magnetic field editing. IEEE Trans. Power Electron. 36, 2710–2719.
Tian, Y., Lai, R., Li, X., Xiang, L., Tian, J., 2020. A combined method for state-of-charge estimation for lithium-ion batteries using a long short-term memory network and an adaptive cubature Kalman filter. Appl. Energy 265, 114789.
2022. Toshiba SCiBTM technology. Available online: https://www.global.toshiba/ww/products-solutions/battery/scib.html.
Trimboli, M.S., Souza, A.K.d., Xavier, M.A., 2022. Stability and control analysis for series-input/parallel-output cell balancing system for electric vehicle battery packs. IEEE Control Syst. Lett. 6, 1388–1393.
Tu, H., Feng, H., Srdic, S., Lukic, S., 2019. Extreme fast charging of electric vehicles: A technology overview. IEEE Trans. Transp. Electrif. 5, 861–878.
Ueda, M., Hirota, T., Hatano, A., 2010. Challenges of Widespread Marketplace Acceptance of Electric Vehicles—Towards a Zero-Emission Mobility Society. SAE Technical Paper.
Vidal, C., Malysz, P., Kollmeyer, P., Emadi, A., 2020. Machine learning applied to electrified vehicle battery state of charge and state of health estimation: State-of-the-art. IEEE Access 8, 52796–52814.
Waag, W., Sauer, D.U., 2013. Adaptive estimation of the electromotive force of the lithium-ion battery after current interruption for an accurate state-of-charge and capacity determination. Appl. Energy 111, 416–427.
Wang, Q., 2019. Battery state of charge estimation based on multi-model fusion. In: Chinese Automation Congress (CAC). pp. 2036–2041.
Wang, Y., Chen, Z., Zhang, C., 2017. On-line remaining energy prediction: A case study in embedded battery management system. Appl. Energy 194, 688–695.
Wang, Z., Du, C., 2021. A comprehensive review on thermal management systems for power lithium-ion batteries. Renew. Sustain. Energy Rev. 139, 110685.
Wang, Q., Jiang, B., Li, B., Yan, Y., 2016a. A critical review of thermal management models and solutions of lithium-ion batteries for the development of pure electric vehicles. Renew. Sustain. Energy Rev. 64, 106–128.
Wang, D., Li, X., Wang, J., Zhang, Q., Yang, B., Hao, Z., 2021. Lithium-ion battery equivalent model over full-range state of charge based on electrochemical process simplification. Electrochim. Acta 389, 138698.
Wang, C.C., Lu, W.J., Wang, S.S., 2014. An on-chip high-voltage current sensor for battery module monitoring. In: IEEE International Conference on IC Design & Technology. pp. 1–4.
Wang, Y., Tian, J., Sun, Z., Wang, L., Xu, R., Li, M., et al., 2020. A comprehensive review of battery modeling and state estimation approaches for advanced battery management systems. Renew. Sustain. Energy Rev. 131, 110015.
Wang, H.F., Xu, Q., 2019. Materials design for rechargeable metal-air batteries. Matter 1, 565–595.
Wang, P., Zhang, X., Yang, L., Zhang, X., Yang, M., Chen, H., et al., 2016b. Real-time monitoring of internal temperature evolution of the lithium-ion coin cell battery during the charge and discharge process. Extreme Mech. Lett. 9, 459–466.
Wei, S., Xu, S., Agrawral, A., Choudhury, S., Lu, Y., Tu, Z., et al., 2016. A stable room-temperature sodium–sulfur battery. Nature Commun. 7, 11722.
Whittingham, M.S., 1976. Electrical energy storage and intercalation chemistry. Science 192, 1126–1127.
Whittingham, M.S., 2004. Lithium batteries and cathode materials. Chem. Rev. 104, 4271–4302.
Whittingham, M.S., 2012. History, evolution, and future status of energy storage. Proc. IEEE 100, 1518–1534.
Winter, M., Barnett, B., Xu, K., 2018. Before li ion batteries. Chem. Rev. 118, 11433–11456.
Winter, M., Möller, K.C., Besenhard, J.O., 2003. Carbonaceous and Graphitic Anodes. Springer, Boston, US.
Wong, Y.S., Chan, C.C., 2012. Vehicle Energy Storage: Batteries. Springer, New York.
Wu, S.-L., Chen, H.-C., Tsai, M.-Y., 2018. Ac impedance-based online state-of-charge estimation for li-ion batteries. Sens. Mater. 30, 539–550.
Wu, Y., Wang, W., Ming, J., Li, M., Xie, L., He, X., et al., 2019. An exploration of new energy storage system: High energy density, high safety, and fast charging lithium ion battery. Adv. Funct. Mater. 29, 1805978.
Wu, B., Widanage, W.D., Yang, S., Liu, X., 2020. Battery digital twins: Perspectives on the fusion of models, data and artificial intelligence for smart battery management systems. Energy AI 1, 100016.
Xi, Z., Wang, R., Fu, Y., Mi, C., 2022. Accurate and reliable state of charge estimation of lithium ion batteries using time-delayed recurrent neural networks through the identification of overexcited neurons. Appl. Energy 305, 117962.
Xia, B., Sun, Z., Zhang, R., Lao, Z., 2017. A cubature particle filter algorithm to estimate the state of the charge of lithium-ion batteries based on a second-order equivalent circuit model. Energies 10, 457.
Xie, Y., He, X-j., Hu, X-s., Li, W., Zhang, Y-j., Liu, B., et al., 2020b. An improved resistance-based thermal model for a pouch lithium-ion battery considering heat generation of posts. Appl. Therm. Eng. 164, 114455.
Xie, Y., Li, W., Hu, X., Zou, C., Feng, F., Tang, X., 2020a. Novel mesoscale electrothermal modeling for lithium-ion batteries. IEEE Trans. Power Electron. 35, 2595–2614.
Xing, Y., He, W., Pecht, M., Tsui, K.L., 2014. State of charge estimation of lithium-ion batteries using the open-circuit voltage at various ambient temperatures. Appl. Energy 113, 106–115.
Xiong, R., Li, L., Tian, J., 2018a. Towards a smarter battery management system: A critical review on battery state of health monitoring methods. J. Power Sources 405, 18–29.
Xiong, R., Sun, W., Yu, Q., Sun, F., 2020a. Research progress, challenges and prospects of fault diagnosis on battery system of electric vehicles. Appl. Energy 279, 115855.

Xiong, R., Yang, R., Chen, Z., Shen, W., Sun, F., 2020b. Online fault diagnosis of external short circuit for lithium-ion battery pack. IEEE Trans. Ind. Electron. 67, 1081–1091.
Xiong, R., Zhang, Y., Wang, J., He, H., Peng, S., Pecht, M., 2018b. Lithium-ion battery health prognosis based on a real battery management system used in electric vehicles. IEEE Trans. Veh. Technol. 68, 4110–4121.
Xu, X., Zhou, D., Qin, X., Lin, K., Kang, F., Li, B., et al., 2018. A room-temperature sodium–sulfur battery with high capacity and stable cycling performance. Nature Commun. 9, 3870.
Xue, T., Fan, H.J., 2021. From aqueous Zn-ion battery to Zn-MnO_2 flow battery: A brief story. J. Energy Chem. 54, 194–201.
Xue, Z., Zhang, Y., Cheng, C., Ma, G., 2020. Remaining useful life prediction of lithium ion batteries with adaptive unscented kalman filter and optimized support vector regression. Neurocomputing 376, 95–102.
Yabuuchi, N., Kubota, K., Dahbi, M., Komaba, S., 2014. Research development on sodium-ion batteries. Chem. Rev. 114, 11636–11682.
Yamaki, J., 2009. Secondary Batteries—Lithium Rechargeable Systems—Lithium-Ion | Overview. Elsevier, Amsterdam.
Yang, X.G., Liu, T., Wang, C.Y., 2021. Thermally modulated lithium iron phosphate batteries for mass-market electric vehicles. Nat. Energy 6, 176–185.
Yao, L., Fang, Z., Xiao, Y., Hou, J., Fu, Z., 2021. An intelligent fault diagnosis method for lithium battery systems based on grid search support vector machine. Energy 214, 118866.
Yao, L.W., Wirun, A., Aziz, J., Sutikno, T., 2015. Battery state of charge estimation with extended Kalman filter using third order thevenin model. Telkomnika 13, 401–412.
Ye, Y., Cheng, K.W.E., 2018. Analysis and design of zero-current switching switched-capacitor cell balancing circuit for series-connected battery/supercapacitor. IEEE Trans. Veh. Technol. 67, 948–955.
Yi, F., Jiaqiang, E., Zhang, B., Zuo, H., Wei, K., Chen, J., et al., 2022. Effects analysis on heat dissipation characteristics of lithium-ion battery thermal management system under the synergism of phase change material and liquid cooling method. Renew. Energy 181, 472–489.
Yi, P., Yixiong, T., Yijie, H., Yuzhe, S., Zhu, T., Zhang, Q., et al., 2014. Renewable energy transmission through multiple routes in a mobile electrical grid. In: Proc IEEE PES Innov Smart Grid Technol Conf. pp. 1–5.
Yu, C., Chau, K.T., 2009. Thermoelectric automotive waste heat energy recovery using maximum power point tracking. Energy Convers. Manage. 50, 1506–1512.
Yu, T., Fu, J., Cai, R., Yu, A., Chen, Z., 2017. Nonprecious electrocatalysts for Li-air and Zn-air batteries: Fundamentals and recent advances. IEEE Nanotechnol. Mag. 11, 29–55.
Zeng, Y., Meng, Y., Lai, Z., Zhang, X., Yu, M., Fang, P., et al., 2017. An ultrastable and high-performance flexible fiber-shaped Ni–Zn battery based on a Ni–NiO heterostructured nanosheet cathode. Adv. Mater. 29, 1702698.
Zhai, C., Luo, F., Liu, Y., 2020. A novel predictive energy management strategy for electric vehicles based on velocity prediction. IEEE Trans. Veh. Technol. 69, 12559–12569.
Zhang, G., Cao, L., Ge, S., Wang, C.Y., Shaffer, C.E., Rahn, C.D., 2014a. In situ measurement of radial temperature distributions in cylindrical Li-ion cells. J. Electrochem. Soc. 161, A1499.
Zhang, N., Dong, Y., Jia, M., Bian, X., Wang, Y., Qiu, M., et al., 2018a. Rechargeable aqueous Zn-V_2O_5 battery with high energy density and long cycle life. ACS Energy Lett. 3, 1366–1372.
Zhang, X., Li, Z., Luo, L., Fan, Y., Du, Z., 2022. A review on thermal management of lithium-ion batteries for electric vehicles. Energy 238, 121652.
Zhang, C., Li, K., Mcloone, S., Yang, Z., 2014b. Battery modelling methods for electric vehicles – a review. In: 2014 European Control Conference (ECC). pp. 2673–2678.
Zhang, Y., Liu, H., Zhang, Z., Luo, Y., Guo, Q., Liao, S., 2020a. Cloud computing-based real-time global optimization of battery aging and energy consumption for plug-in hybrid electric vehicles. J. Power Sources 479, 229069.
Zhang, Y., Song, W., Lin, S., Feng, Z., 2014c. A novel model of the initial state of charge estimation for $LiFePO_4$ batteries. J. Power Sources 248, 1028–1033.
Zhang, X., Tang, Y., Zhang, F., Lee, C.S., 2016. A novel aluminum–graphite dual-ion battery. Adv. Energy Mater. 6, 1502588.
Zhang, R., Xia, B., Li, B., Cao, L., Lai, Y., Zheng, W., et al., 2019a. State of the art of lithium-ion battery SOC estimation for electrical vehicles. Energies 11, 1820.
Zhang, Y., Xiong, R., He, H., Pecht, M.G., 2019b. Lithium-ion battery remaining useful life prediction with Box–Cox transformation and Monte Carlo simulation. IEEE Trans. Ind. Electron. 66, 1585–1597.
Zhang, J., Zhang, L., Sun, F., Wang, Z., 2018b. An overview on thermal safety issues of lithium-ion batteries for electric vehicle application. IEEE Access 6, 23848–23863.
Zhang, J., Zhong, H., Cui, J., Xu, Y., Liu, L., 2020b. An extensible and effective anonymous batch authentication scheme for smart vehicular networks. IEEE Internet Things J. 7, 3462–3473.
Zhao, M., Li, B.Q., Zhang, X.Q., Huang, J.Q., Zhang, Q., 2020. A perspective toward practical lithium–sulfur batteries. ACS Cent. Sci. 6, 1095–1104.
Zhao, Y., Liu, P., Wang, Z., Zhang, L., Hong, J., 2017. Fault and defect diagnosis of battery for electric vehicles based on big data analysis methods. Appl. Energy 207, 354–362.
Zhou, W., Zheng, Y., Pan, Z., Lu, Q., 2021. Review on the battery model and SOC estimation method. Processes 9, 1685.
Zhu, J., Knapp, M., Darma, M.S.D., Fang, Q., Wang, X., Dai, H., et al., 2019. An improved electro-thermal battery model complemented by current dependent parameters for vehicular low temperature application. Appl. Energy 248, 149–161.
Zhu, J., Li, Y., Yang, B., Liu, L., Li, J., Yan, X., et al., 2018. A dual carbon-based potassium dual ion battery with robust comprehensive performance. Small 14, 1801836.
Zou, C., Hu, X., Dey, S., Zhang, L., Tang, X., 2018a. Nonlinear fractional-order estimator with guaranteed robustness and stability for lithium-ion batteries. IEEE Trans. Ind. Electron. 65, 5951–5961.
Zou, C., Zhang, L., Hu, X., Wang, Z., Wik, T., Pecht, M., 2018b. A review of fractional-order techniques applied to lithium-ion batteries, lead–acid batteries, and supercapacitors. J. Power Sources 390, 286–296.