Chapter 9

Battery Management Technologies in Hybrid and Electric Vehicles

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Hybrid electric vehicles (HEVs) and electric vehicles (EVs) have been advocated by global governments' policies in recent decades. Besides combating the climate crisis and urban air pollution, great contributions of developing the HEVs and EVs have been identified to accelerate the process of green transportation and smart city. Battery management is one of the most crucial functions for HEVs and EVs. It can ensure the safe operation and optimize the performance of EV batteries. This chapter discusses the mainstream technologies of battery management in HEVs and EVs. Wherein, battery management technologies, including battery modeling, battery state estimation, safety prognostic (such as thermal management), and fault diagnosis, are elaborated in detail. Among them, the data-driven method is most effective and promising for battery state estimation (such as for state of charge and state of temperature) and health diagnosis or prognostics with impressive accuracy. Besides, some emerging management technologies, including multi-model co-estimation, artificial intelligence, cloud computing technology, and blockchain technology, are briefed, which can play a significant role in coordinating the information and energy flows in a vehicular information and energy internet.

9.1 Background

Conventional mobility has been experiencing a historic transition from the era of internal-combustion-engine vehicles to another of hybrid electric vehicles (HEVs) and electric vehicles (EVs) [1]. The developments of HEVs and EVs will make great contributions to promoting the accomplishment of carbon neutrality, green mobility, and smart city. Furthermore, they have numerous advantages of improving urban air quality, alleviating energy shortages, and combating the climate crisis. Therefore, national governments have put in efforts to advocate by making policies. Typically, the United States announced that the sales share of EVs should reach 50% by 2030. China's New Energy Vehicle Industrial Development Plan for 2021 to 2035 ("Plan 2021–2035") aims to build a green, robust, and internationally competitive auto industry [2]. Future EVs may evolve into a power and information interface, which can help users to perform energy interaction with the modern power grid by vehicle-to-grid operation and information interaction with the cloud by wireless communication, respectively [3, 4]. However, advanced battery management is essential for achieving the above functions in a vehicular information and energy internet (VIEI).

As energy storage devices, batteries and supercapacitors are commonly used in EVs and HEVs. Compared with the battery, the supercapacitor possesses much higher specific power (W kg^{-1}) but suffers from much lower specific energy (Wh kg^{-1}), thus improving the transient power handling capability [5]. As a result, the battery serves to provide the majority of energy capacity thanks to its high energy density, while the supercapacitor usually serves 5% of energy capacity only due to its high cost and large volume. For automobile applications, the main challenges are on three key performance indicators of (1) safety issues, (2) energy density, and (3) fast-charging capability. Accordingly, lithium-ion batteries (LIBs) outperform the nickel-based batteries and lead-acid batteries, hence dominating the current battery industry for HEVs and EVs [6, 7].

Table 9.1 Common lithium-ion batteries

Cathode	Anode
• $LiCoO_2$	• $Li_4Ti_5O_{12}$
• $LiMn_2O_4$	• Soft carbon
• $LiFePO_4$	• Hard carbon
• $Li[Ni_xCo_yMn_z]O_2$ (such as $Li[Ni_{0.8}Co_{0.1}Mn_{0.1}]O_2$), and $Li[Ni_{0.6}Co_{0.2}Mn_{0.2}]O_2$	• Graphite • Silicon/graphite
• $Li[Ni_xCo_yAl_z]O_2$ (such as $Li[Ni_{0.8}Co_{0.15}Al_{0.05}]O_2$)	

Divided by electrode materials for anode and cathode, the common types of LIBs are listed in Table 9.1. Superior to nickel-based batteries and lead-acid batteries, all these LIBs can provide high energy density for HEVs and EVs [8]. Although the lithium-titanium battery suffers from relatively lower energy density than the state-of-the-art LIBs do, it has a much better fast-charging capability thanks to its good charging acceptance. Plenty of battery cells are connected in series for meeting the requirement of voltage level and in parallel for improving the energy capacity of a battery pack in EVs. Due to the manufacturing difference, the cell balancing, thermal management, and aging issue are required to be concerned during the battery charging and discharging. Optimization of charging and discharging profiles can facilitate the battery to maintain high energy capacity and long remaining useful life. Battery management technology can protect the battery from various faults and perform optimal battery performances.

9.2 Battery Management System

9.2.1 Key Concepts

High-energy batteries will play a significant role in powering EVs. Therefore, their safety, reliability, and efficient operations are the main concerns of consumers. To achieve these goals, a battery management system (BMS) is required to monitor and manage the battery conditions. Some key concepts regarding battery management are introduced as follows.

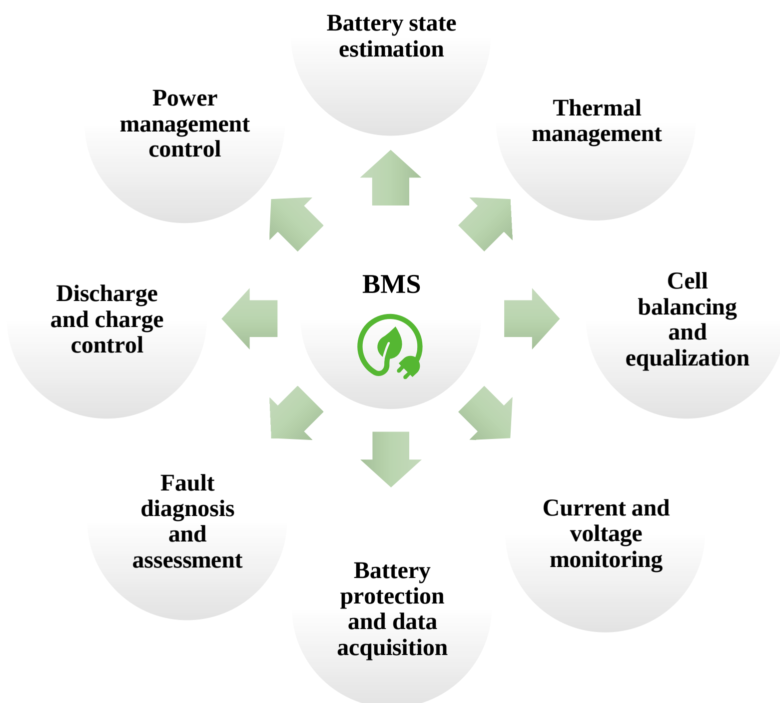

Figure 9.1 Battery management system in hybrid and electric vehicles.

9.2.1.1 State of Charge

There are many definitions of state of charge (SoC). In this work, the SoC is quantified as the percentage of the reserve capacity to the rated capacity under the same specified condition. For example, the 100% or 0% SoC indicates that the battery is fully charged or discharged, respectively. Besides the safe and reliable operation, the SoC aids to determine the optimal strategies for charging and discharging. Furthermore, accurate estimation of SoC can be used to predict the remaining useful life (RUL).

9.2.1.2 State of Health

Importantly, the state of health (SoH) signifies a figure of merit of battery conditions compared to its ideal conditions. It can be derived by many parameters, such as internal resistance, AC impedance, battery capacity, power density, and discharge rate. The most common definition of SoH is the ratio of the maximum available capacity to the rated value of the battery. The 100% SoH means a fresh battery. While a battery with less than 80% SoH will be out of use due to the capacity of below 80% of the rated capacity. Another way to estimate SoH is to compare the internal resistance with its initial value. If the internal resistance grows to 1.3 times its initial value, the battery should also be retired.

9.2.1.3 State of Temperature

State of temperature (SoT) is a crucial factor for the thermal management of batteries.

High operation temperature will reduce both the cycle life and the performance of batteries. Worse still, the battery will cause fire and explode due to thermal runaway. On the other hand, low operation temperature may disable the battery charge, and thus battery preheating is necessary. Although the battery surface temperature can be readily measured by thermal sensors, the SoT is more relevant to the internal temperature that directly influences the electrochemical conditions.

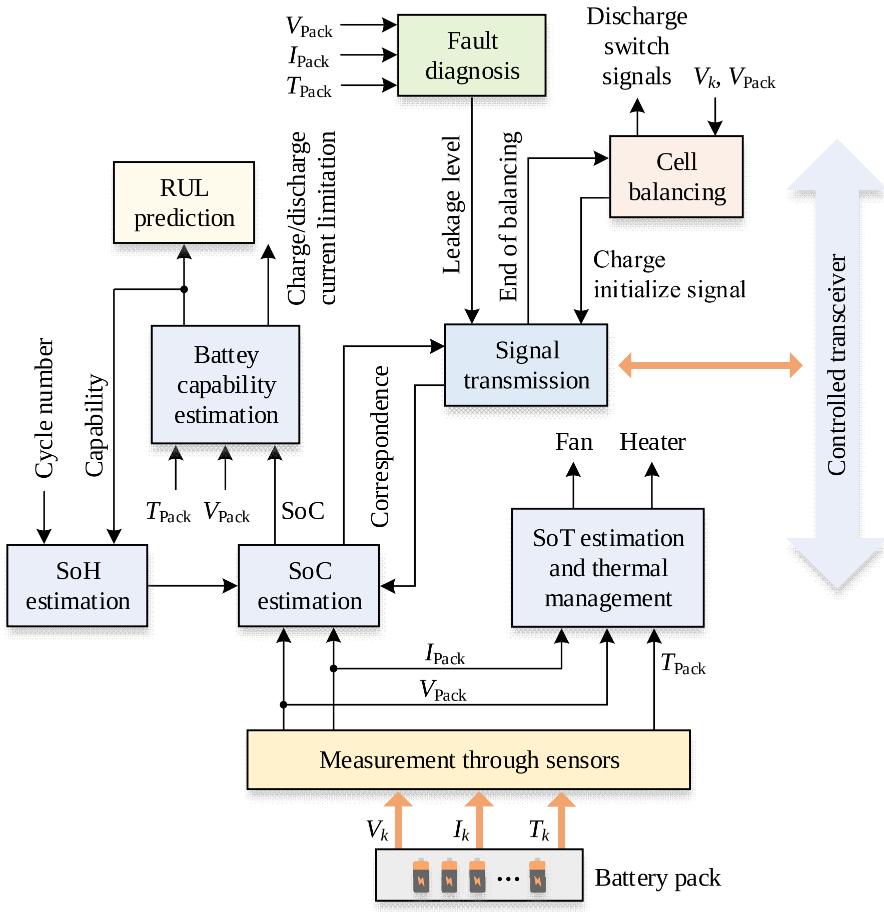

Figure 9.2 Block diagram of battery management system.

9.2.1.4 State of Function

State of function (SoF) is to describe how a battery can meet the actual demand. It relates to many factors, such as SoC, SoH, SoT, and charge/discharge history. The prediction of SoF is quite significant for the reliable operation of the EV battery system.

9.2.1.5 State of Balance

Due to the difference in the manufacturing process, the concept of the state of balance (SoB) is used to define the battery cell-to-cell consistency. Once with imbalance, overcharging may happen in a cell after all others get fully charged, which may cause distortion, leakage, rise in pressure, and even explosion. In contrast, over-discharging may occur in a cell after all others get fully discharged, which will shorten the cycle life. Accordingly, the detection and management of SoB will benefit the cell balancing in a battery pack.

9.2.2 Basic Principles

Physical damage, performance degradation, and thermal runaway will lead to battery malfunctions or catastrophic failure. A BMS is deployed to prevent the EV battery from experiencing such adverse cases. The BMS is a complex system including data acquisition, modeling, state estimation, charging control, thermal management, fault diagnosis, and communication. The parameters of voltage, current, and temperature of each cell are sensed and processed in a BMS. Wherein, the data handling is massive, and the data communication is usually based on a controller area network transferring data to microprocessors and other units. Accordingly, the main functions of the battery management system (BMS) are summarized as shown in Figure 9.1, and they can be elaborated as follows.

(1) Battery state estimation, including SoC, SoH, SoT, etc.
(2) Thermal management to avoid thermal runaway in batteries.
(3) Fault diagnosis and assessment, battery protection, and data acquisition.
(4) Cell balancing and equalization.
(5) Coordination with vehicle control unit and other units including the power management and charge-discharge control [9].

As a series of advanced functions are integrated into a BMS, Figure 9.2 shows a whole block diagram of a BMS to introduce the correlation between management functions and data communication [10]. A block of controlled transceiver serves for transmitting and receiving data. The parameters of voltage V_k, current I_k, and temperature T_k are measured at the cell level by using a sensing block. These parameters are used for battery state estimation of SoC, SoH, SoT, and so on. For battery thermal management, the fan or heater will be controlled to maintain the battery temperature within an optimal range. Meanwhile, the battery capacity estimation can serve to assess the energy capacity, diagnose the health status, and produce the limitations of charge-discharge current. Besides, the cell equalizer is in charge of cell balancing, and multi-dimensional constraints will be generated to prevent the irregularities of over-charge and over-discharge in partial cells. A block of fault diagnosis offers crucial functions of fault prognostics and troubleshooting, thus guaranteeing the operating safety of the battery.

In Figure 9.3, the battery management technologies mainly include four primary parts: (1) battery modeling, (2) battery state estimation, (3) safety prognostics and health diagnosis, and (4) emerging management technologies. Wherein, the data-driven method is currently recognized as one of the most promising methods for battery management. The emerging management technologies can be further divided into four secondary parts: (1) multi-mode co-estimation, (2) artificial intelligence technology, (3) cloud computing technology, and (4) blockchain technology. In the following content, all relevant technologies will be introduced one by one.

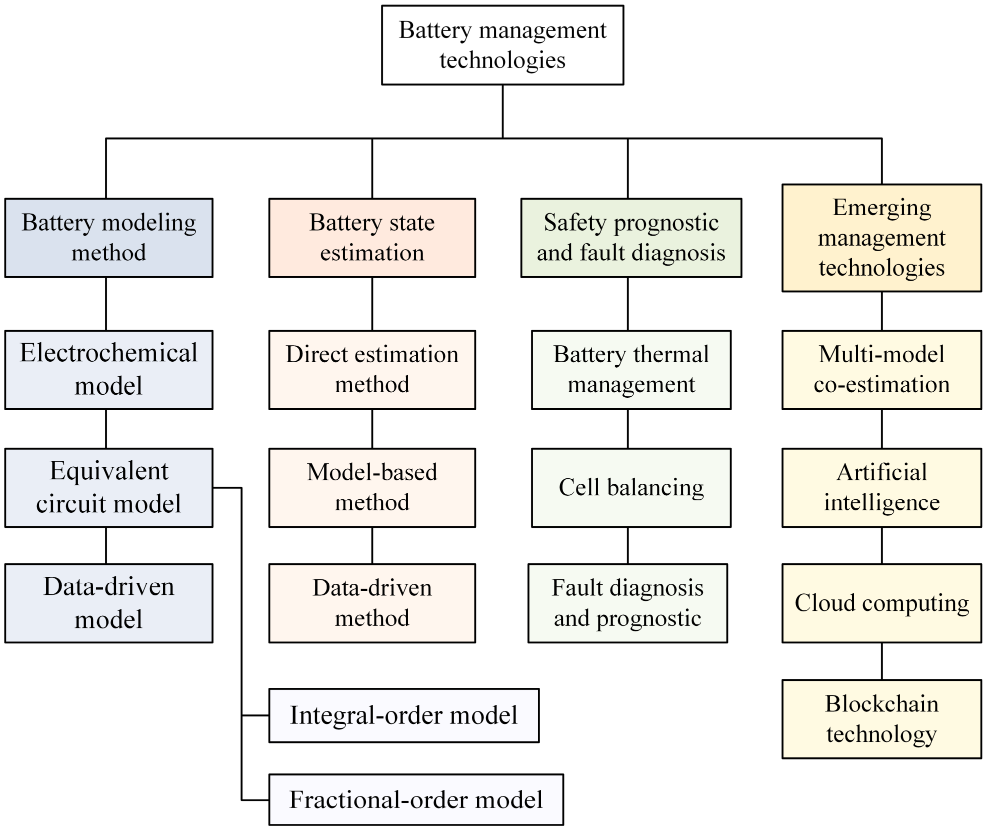

Figure 9.3 Battery management technologies in hybrid and electric vehicles.

9.3 Battery Modeling Method

To collect the experiment data, Figure 9.4 shows a battery testing system for the cycling test of battery cells or modules. This battery testing system mainly contains the following five parts: (1) Battery cells or modules, (2) a thermal chamber, (3) a switch board, (4) a battery cycle tester, and (5) a computer with ethernet cables. The computer is in charge of battery state monitoring and data acquisition under controlled ambient temperatures. The dataset from battery cycling is used to build or train the battery model that can extract and redefine the features of battery cells or modules. On top of the battery model, the battery state estimation, fault diagnosis, and health prognostic can be achieved with the help of various advanced algorithms. The electrochemical impedance spectroscopy (EIS) technique is usually used to measure the alternating-current (AC) impedance at different frequencies. Meanwhile, the Nyquist plot of AC impedances may assist to choose a suitable type of battery model that is an important prerequisite for battery management.

The main significances of battery modeling methods are summarized as shown in Figure 9.5 for battery management technologies. To offer an accurate representation of a battery, three battery modeling methods are introduced in detail, including (1) electrochemical models, (2) equivalent circuit models (ECMs), and (3) data-driven models. Figure 9.6 shows the current evolution trends of three battery modeling approaches for battery management in EV applications [11]. Thanks to the high model accuracy and acceptable complexity, the data-driven method is recognized as one of the most promising methods at the current stage.

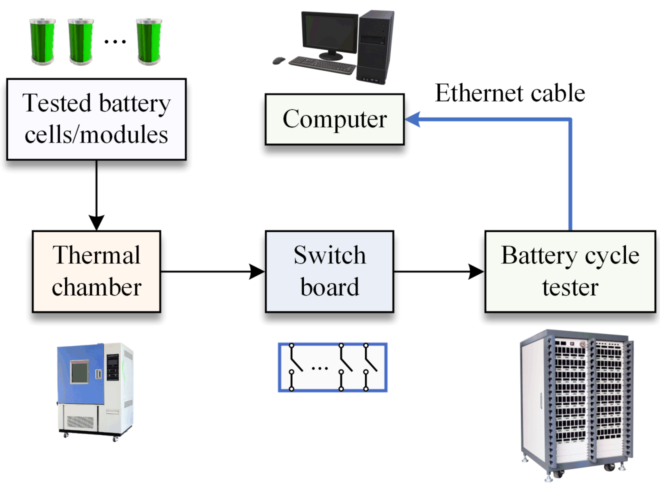

Figure 9.4 Battery testing system for experiment data collection.

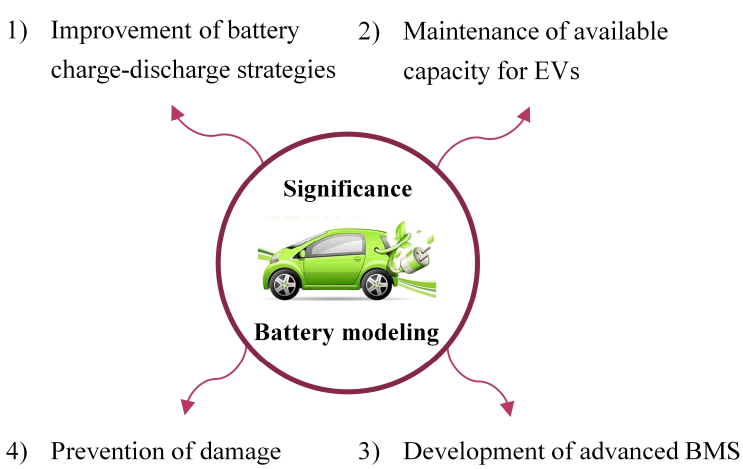

Figure 9.5 Main significances of battery modeling for battery management.

9.3.1 Electrochemical Model

Battery, exhibited as an electrochemical device, can be represented by physics-based approaches, which can exhibit a consistency of external characteristics between the practical battery and its model [12]. Wherein, by ignoring the influence of concentration distribution and potential on the terminal voltage, the single-particle model in Figure 9.6 (bottom) owns the features of good simplicity and mature technology but relatively low accuracy [13]. According to the complex non-linear chemical reactions, the electrochemical models are to address the cores of batteries at the microscopic scale. Thus, there exists no doubt that these models represent the most accurate and detailed information about a battery. However, the main barriers blocking the widespread use of electrochemical models are two aspects. On the one hand, global optimization approaches should be used to solve plenty of non-analytical solutions. On the other hand, the correlation between control equations and boundary conditions suffers from a strong coupling [12]. Besides the huge memory requirements and computational burdens, the optimization procedure is inevitably time-consuming due to the concern of convergence rate. Fruitful research works are focusing on the development of battery electrochemical models, such as a pseudo-two-dimensional model [14] and a reduced-order electrochemical model [15]. Nevertheless, the variations of battery temperatures and aging effects will significantly increase the difficulty in improving the accuracy of battery modeling. Accordingly, a thermal-electrochemical model develops into a research hotspot recently [16].

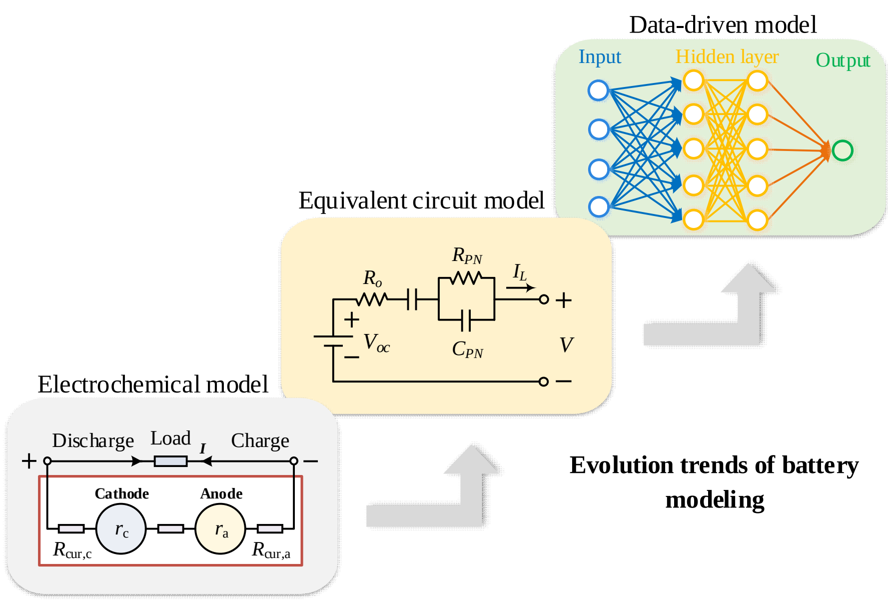

Figure 9.6 Evolution trends of battery modeling for battery management.

9.3.2 Equivalent Circuit Model

As aforementioned, the complexity of the electrochemical model limits its popularization and practicality, thus leading researchers to investigate another model, namely, the equivalent circuit models (ECMs). Four basic ECMs are shown in Figure 9.7 [17], which adopt the lump resistor(s), inductor(s), or capacitor(s) for battery representation. Hence, the basic electrical components are used to build such a kind of battery model, which can imitate the battery behaviors and thus increase the model applicability. The ECMs are recognized as a more straightforward method by researchers, which can help the BMS control the power flow of EV batteries. There are two promising types of high-order ECMs: (1) Integral-order models (IOMs), and (2) fractional-order models (FOMs), as shown in Figure 9.8(a) and Figure 9.8(b) [3], respectively.

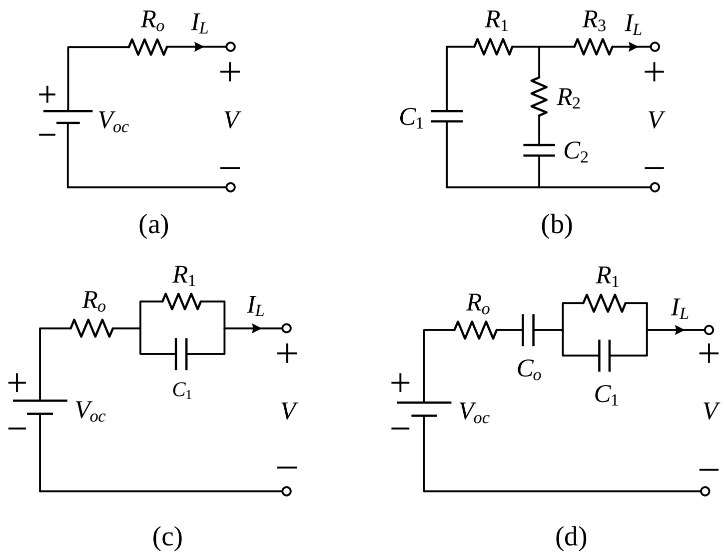

Figure 9.7 Equivalent circuit models of battery cell.

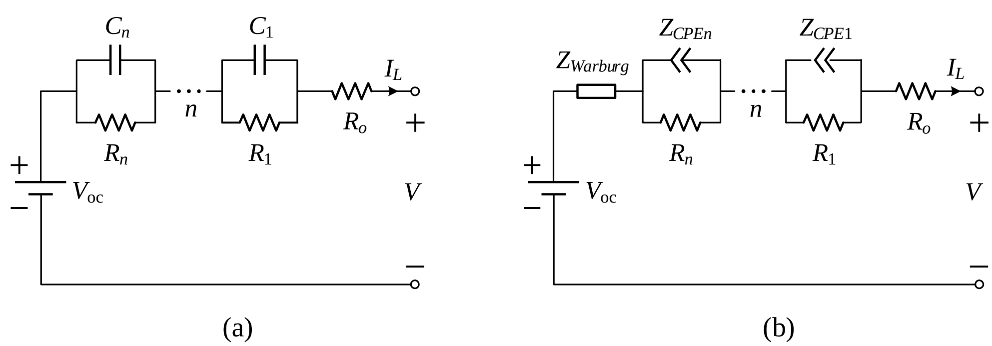

Figure 9.8 High-order equivalent circuit models of battery cell. (a) Integral-order equivalent circuit model. (b) Fractional-order equivalent circuit model.

9.3.2.1 Integral-Order Model

It should be noted that some basic ECMs in Figure 9.7 can be seen as the IOMs. The Rint model in Figure 9.7(a) has the simplest form using one voltage source and one resistor in series. However, the phenomenon of internal polarization fails to be exhibited in this Rint model [18]. Figure 9.7(c) shows a Thevenin model with an additional parallel resistor-capacitor (RC) circuit. For presenting the battery dynamic characteristics better, the high-order IOM in Figure 9.8(a) adds two or more RC circuits to improve the model accuracy [19]. The advantages of IOMs are the fewer model parameters and faster simulation speed, while the disadvantages are the unreliable extrapolation and the failed prediction of battery's internal electrochemical states. Higher-order IOMs add more RC circuits, which is at the expense of higher difficulty in model parameter identification. All the performances of model accuracy, complexity, and computational burden shall be considered comprehensively for confirming the optimal number of RC circuits.

9.3.2.2 Fractional-Order Model

Within the whole frequency range, the IOMs using RC circuits only cannot indicate the internal electrochemical characteristics, in particular for the middle frequency range. To deal with this issue, the FOMs were suggested to replace the capacitor in the RC circuits by using a constant phase element [20]. As a result, the suggested FOMs can improve the model accuracy for the imitation of physical phenomena in a whole frequency range. However, the improvement of model accuracy sacrifices the simulation speed and adds the model complexity of the ECMs. Once a proper ECM is determined, such as the FOM, the parameters of the battery model can be figured out by using the methods of EIS techniques [21]. Thus, the accurate FOMs can simulate a practical battery and predict battery states precisely, thus conducting battery management effectively.

9.3.3 Data-Driven Model

As one of the most effective methods, data-driven models are developed according to the battery's external characteristics. This kind of battery model can be treated as a black-box model. The use of experiment data can train out a mathematical model that can offer an advantage of good reflection to the batteries' nonlinear electrochemical reactions. The data-driven modeling method can extract the hidden information effectively from the experiment dataset. Also, the generalization capability of this data-driven modeling method is superior to those of others for battery state estimation [12]. With the rapid development of microprocessors and computer science, the data-driven modeling method has been attracting more and more attention from researchers recently. Consequently, rich outcomes have been achieved in this hot topic. For example, machine learning methods including support vector machines [22] and neural networks [23] have been actively explored for battery management, especially for battery state estimation.

Table 9.2 Critical comparisons of battery modeling methods

Battery modeling methods	Electrochemical model	Equivalent circuit model	Data-driven model
Model accuracy	☆☆ (medium)	☆☆	☆☆☆
Model interpretability	☆ (low)	☆☆☆	☆
Model complexity	☆☆☆ (high)	☆	☆☆
Typical applications	Battery design	Battery state estimation of SoC and state of power	Battery state estimation of SoH, SoT, and RUL

To provide critical comparisons of the aforementioned three battery modeling methods, Table 9.2 lists their key features of model accuracy, interpretability, complexity, and typical applications [20, 24]. As listed in Table 9.2, the electrochemical model can achieve medium accuracy but suffer from high model complexity. The ECM has low complexity and high interpretability, but it fails to increase the model accuracy significantly. The data-driven model is identified with outstanding merits because the model accuracy is highest while the model complexity is acceptable as compared with the others. Importantly, the data-driven modeling method can also exhibit superior performances even taking into account the variations of temperature and aging effects. It should be noted that the use of different training datasets and algorithms will influence the performances of data-driven modeling methods. Furthermore, the implementation time is also another key performance indicator to evaluate the battery modeling methods. Nevertheless, the data-driven modeling method is believed as a potential approach for future battery management, and technological breakthroughs will be made to improve this battery modeling method continuously.

9.4 Battery State Estimation

Generally, there are three methods for battery state estimation as follows.

(1) The direct estimation method can be further split into the direct measurement method and the look-up table method.

(2) The model-based method includes two subcategories: 1) Filter-based method, and 2) observer-based method.

(3) The data-driven method can integrate with other intelligent technologies, such as machine learning and neural network, for battery state estimation of SoC, SoH, SoT, and so on.

9.4.1 Direct Estimation Method

It is a straightforward method to conduct the battery state estimation. The open-circuit voltage, internal resistance, electromotive force, or EIS of a battery can be chosen to be used in the direct estimation method. Wherein, a typical estimation method is to measure the open-circuit voltage and create a parameter table. Subsequently, this open-circuit voltage estimation method will look up the established table and find the SoC. It is simple but accurate enough [25]. Because the estimation errors are inevitable due to the hysteresis characteristics of a battery, these estimation errors are not desirable in high-precision applications, such as for the aviation and military areas. In another way, the internal resistance of a battery can be used for predicting the battery states, such as SoC, and capacity, but its accuracy is not acceptable due to the low value of battery internal resistance [26]. Although the SoC can be predicted more straightforwardly by using an ampere-hour integral approach, the sensor errors will be inevitably accumulated to increase the final estimation errors.

Significantly, the influences of temperature and aging may reduce the accuracy of battery state estimation. Also, the surface temperature of a battery can be readily sensed and collected, while the internal temperature cannot. To solve this problem, temperature sensors are implanted between the cell internal layers to estimate the SoT inside a battery. In such a way, the manufacturing difficulty and safety issues should be highly concerned. As a potential direction of technical breakthroughs, the joint estimation method integrating the direct estimation deserves to be explored to improve the state estimation performances, especially for estimation precision and robustness.

Table 9.3 Surveys and comparisons of state estimation methods

State estimation methods	Detailed approaches	Advantages	Disadvantages
Direct estimation method	• Internal resistance • Open circuit voltage • Impedance spectroscopy • Electromotive force • Embedding sensors	✓ Low computational burden ✓ Direct and simple for implementation ✓ Joint estimation with model-based methods	× Off-line × Inaccurate in practice × Long resting time × Sensitivity to sensor precision
Model-based method	• Filter-based method ➢ Particle filter ➢ Kalman-filter • Observer-based method ➢ H-infinity observer ➢ Sliding mode observer ➢ Luenberger observer	✓ Insensitive to initial state ✓ Online and real-time ✓ High accuracy ✓ Fast convergence ✓ Robustness to sensor noise	× High computational burden × Precision depends on model accuracy × Requiring more experiment data and validation
Data-driven method	• Neural network • Machine learning • Genetic algorithm • Support vector machine • Fuzzy logic	✓ Less pre-tests required ✓ Independent of model ✓ High accuracy ✓ Robustness to conditions and noises ✓ Dynamic data-driven electrothermal model for predicting SoT, SoH, etc.	× Relying on training samples × High computational burden × Requirements on efficiency and portability of algorithms
Cloud computing	• Vehicular cloud computing technology	✓ Ability for running complex algorithms ✓ Collaboration with cloud computing centers ✓ Leveraging resources of participating EVs	× More complicated due to high mobility and wide range of EVs × Leaking information and compromising privacy possibly
Blockchain technology	• Private blockchain • Consortium blockchain	✓ Public ledger system ✓ Data sharing and tracking ✓ Protecting user privacy ✓ More driving data	× Not mature technology × Some research gaps (latency and throughput) × Expecting to improve usability

9.4.2 Model-Based Method

For battery state estimation, the filter-based methods mainly include the particle filter approach and the Kalman filter approach, while the observer-based methods mainly involve the H-infinity observer, sliding mode observer, and Luenberger observer. Both kinds of model-based methods are developed to improve the estimation accuracy and reliability. It is preferable to use a highly accurate model while with a relatively low computational burden. To estimate the SoC, SoH, or RUL, an adaptive extended Kalman filter incorporated with a Thevenin ECM was designed and verified against dynamic temperature variations [27]. Also, to estimate both the surface temperature distributions and internal temperature distributions, thermal models of a battery were actively designed by integrating with the Kalman filter. Besides the Kalman filter, the particle filter-based method has been applied to the battery state estimation. It is suitable for dealing with nonlinear and non-Gaussian problems. Therefore, the health prognosis can be achieved readily by using the particle filter-based method. Promisingly, the joint Kalman particle filter method and multi-model particle filter method are actively explored to predict the RUL and battery capacity, which can achieve higher prediction accuracy and stability.

The observer-based method relies on a high-precision observer for predicting battery states. Wherein, the H-infinity observer, sliding mode observer, Luenberger observer, and proportional-integral observer are developed for advancing the model-based methods, respectively. For example, in a fractional-order state estimator, the Luenberger observer and sliding mode observer were in charge of guaranteeing the error convergence and robustness improvement, respectively [28]. Besides, an H-infinity observer was adopted to estimate the SoC by observing the electrochemical impedance [29]. On the other hand, some other types of observers, such as nonlinear observers, have also been studied for battery state estimation. Finally, further improvements of estimation precision and robustness are desired with an acceptable computational cost.

9.4.3 Data-Driven Method

As a black-box method, the data-driven method avoids the need of prior knowledge of electrochemical mechanisms, which can directly extract the correlations hidden in the measured dataset. The experiment dataset can train the battery model for state estimation, fault diagnosis, and health prognostic. The data-driven methods include several advanced approaches of the artificial neural network [23], machine learning technique, genetic algorithm, support vector machine [22], etc. As technology advances, more scholars and institutes recognized that the data-driven electrothermal model is a potential method for battery state estimation. It will well integrate both the battery thermal model and battery electric model by considering the influences of different temperatures. This data-driven electrothermal model will be used to predict the battery capacity, RUL, and SoT in real-time, and it can generate the optimal current reference for battery charging control.

The capacity degradation, SoT, and SoH are highly related to the reliable operation of EV batteries. Possible failures of state prediction may cause battery malfunctions and even more severe problems, such as battery leakage, explosion, or fire. Therefore, early prediction of these key states is very significant for ensuring the battery’s safe operation. Until now, many research works are focusing on these data-driven methods. For example, a data-driven method integrated with machine learning technology was used to estimate the cycle life [30], while a joint data-driven could suppress the estimation errors of SoH online [31]. A machine learning framework was implemented to reduce the early-cycle prediction errors of RUL effectively, and it contains three steps including (1) feature extraction, (2) feature selection, and (3) state prediction [32]. It is worth noting that the variations of operating conditions (such as temperature), cell voltage imbalances and uneven aging effects will significantly increase the difficulty and decrease the accuracy of data-driven state estimation.

Table 9.3 provides the in-depth surveys and comparisons of battery state estimation methods including the aforementioned three methods, cloud computing method, and blockchain technology [3, 33]. As listed in Table 9.3, their detailed approaches, advantages, and disadvantages are discussed in detail. The main comments can be summarized as follows:

(1) The direct estimation method is straightforward but mainly suffers from low accuracy and robustness in practice.

(2) The model-based method has better accuracy and robustness that highly rely on the model accuracy, experiment data, and computational ability.

(3) The data-driven method can be trained by a huge dataset and owns better accuracy and robustness to the selections of models and the variations of operating conditions.

(4) As the rapid development of communication technology and computer science, cloud computing and blockchain technology are identified as very potential methods for battery state estimation for a large number of EVs and HEVs.

In the next decade, the reduction of computational cost and the acceleration of processing rate are both important directions for future technological breakthroughs. The introduction of cloud computing and blockchain technology can help share the computational capability and vehicular data information among EVs, HEVs, and vehicular internet.

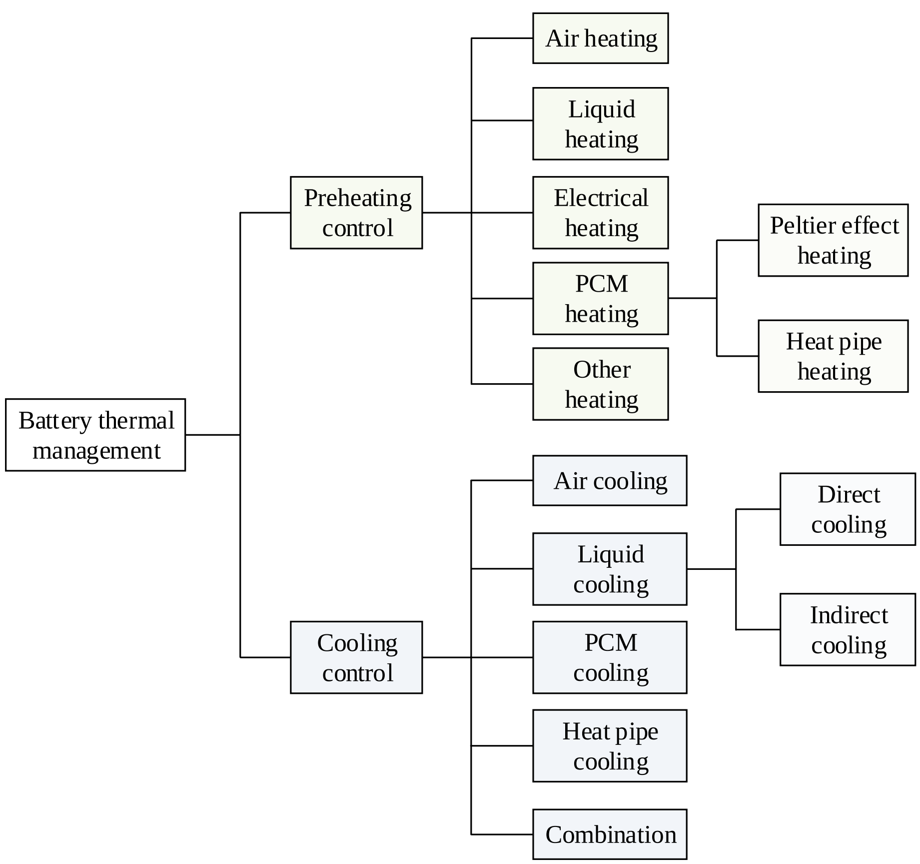

Figure 9.9 Battery thermal management for hybrid and electric vehicles.

9.5 Safety Prognostic and Fault Diagnosis

Battery health will determine the safety of EV driving. There are many measures for maintaining the battery health so as to perform its optimal performance. First, to ensure the reliability of electric populations, a battery thermal management system (BTMS) is a very important part to prevent the occurrence of thermal runaway in a BMS. Second, cell balancing may protect the cells from experiencing the imbalance of voltage, capacity, or SoC, which is significant for improving the uneven cell aging effects. Third, fault diagnosis and prognostic are essential for troubleshooting various faults in EV batteries [34]. More significantly, the real-time online diagnosis and prognostic are preferable and deserve to be developed for a smart BMS.

9.5.1 Battery Thermal Management

A BTMS is deployed to monitor and manage the temperature of batteries within an optimal range. For example, LIBs require a typical temperature of 20 °C~40 °C [35]. Figure 9.9 shows the battery thermal management methods for EVs and HEVs, including the typical preheating control and cooling control. Wherein, the preheating methods can be further divided into five approaches: (1) Air heating, (2) liquid heating, (3) electrical heating, (4) phase change material (PCM) heating, and (5) other heating. On the other hand, the cooling methods can also be classified into five approaches: (1) Air cooling, (2) liquid cooling, (3) PCM cooling, (4) heat pipe cooling, and (5) combination. The main principle, advantages, and disadvantages of each heating or cooling method have been presented in detail in [36, 37].

The BTMS is quite important for the temperature regulation and uniformity of cells [17]. Reliable thermal management enables the battery’s safe operation and avoids the malfunctions of leakage, fire, and explosion. In contrast, abnormal temperatures will greatly harm the battery's performance, including its energy capacity and cycle life. Hence, these harms are discussed in terms of different thermal conditions as follows.

(1) If the temperature is over low, the LIBs will generate the lithium dendrites. The fault of short circuit, starting failure, or others occurs possibly [36]. Meanwhile, the battery internal resistance may increase, and the inactivity of electrochemical reactions will be aggravated, thus downgrading the battery performances inevitably.

(2) If the temperature is over high, a thermal runaway may happen inside the battery, thus causing the fire and explosion.

(3) If the non-uniformity of battery temperature happens, partial degradation and uneven cell aging will be worsened and accelerated.

9.5.2 Cell Balancing

Cell balancing can buy the extra run time and battery life. Generally, the cell balancing methods include (1) voltage balancing, (2) capacity balancing, and (3) SoC balancing. Accordingly, their algorithms can be mainly classified into the following three kinds: (1) voltage uniformity approach, (2) capacity uniformity approach, and (3) SOC uniformity approach [38]. The manufacturing differences and thus reaction differences can hardly be avoided among all cells, which may lead to the inconsistency of cells’ voltages, SoCs, aging rates, and capacity fade rates [39]. Therefore, cell balancing is the same important as thermal management. Otherwise, the severe inconsistency will cause battery leakage, fire, or explosion, like the thermal runaway. Figure 9.10 shows two typical circuits of (1) passive cell equalizer, and (2) active cell equalizer [39]. Wherein, the passive cell equalizers use the shunting resistors to realize the cell balancing. Differing from the use of switches, they can be further divided into two subcategories: (1) Passive cell equalizer using fixed shunting resistors, and (2) passive cell equalizer using switched shunting resistors. Their circuits are shown in Figure 9.11(a) and Figure 9.11(b), respectively. These kinds of cell equalizers have the advantage of low complexity but suffer from the disadvantage of low efficiency due to the joule loss.

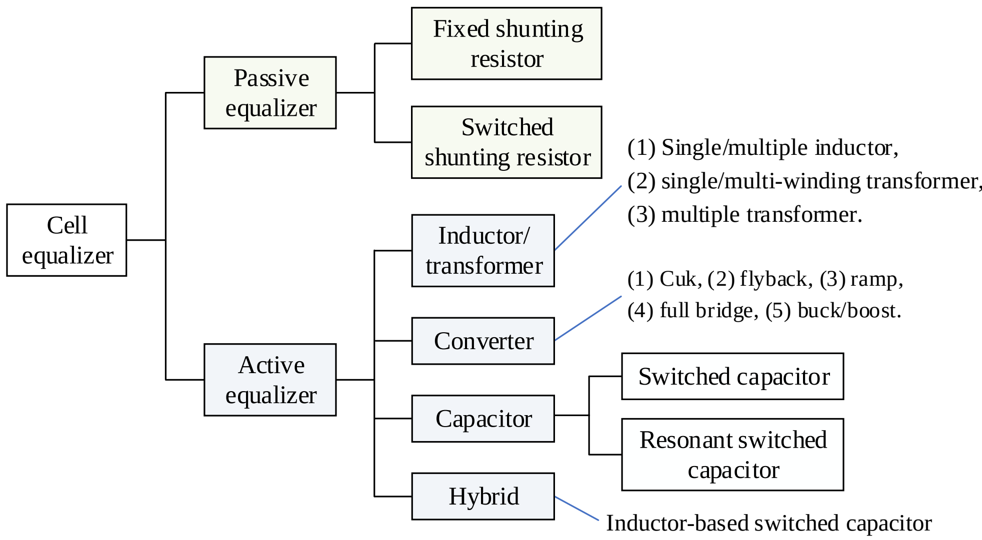

Figure 9.10 Categories of cell equalizers for electric vehicle batteries.

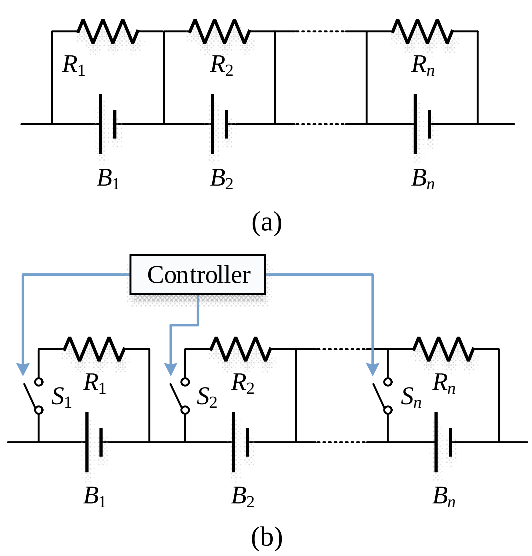

Figure 9.11 Passive cell equalizers for voltage balancing. (a) Fixed shunting resistor. (b) Switched shunting resistor.

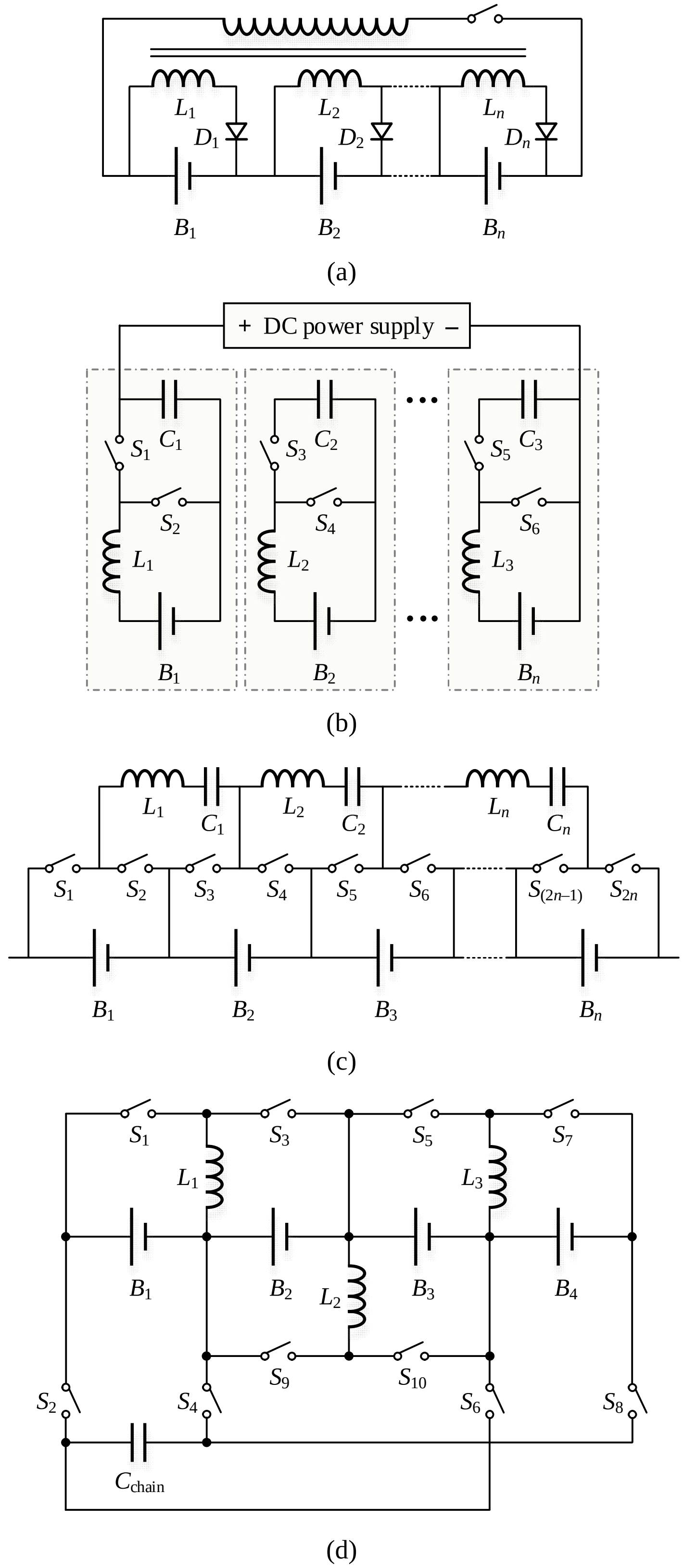

Figure 9.12 Active cell equalizers for voltage balancing. (a) Multi-winding transformer. (b) Buck/boost. (c) Quasi-resonant converter. (d) Inductor-based switched capacitor.

In contrast, the active cell equalizers improve the system efficiency and operation stability effectively but at the expense of slightly adding system complexity. As shown in Figure 9.10, these active cell equalizers are further classified into four subcategories: (1) Inductor/transformer-based types, (2) converter-based types, (3) capacitor-based types, and (4) hybrid types. Typically, their representative circuits are shown in Figure 9.12(a)–(d), respectively. Further detailed types of cell equalizers are given in Figure 9.10. As a supplement, the switched capacitor (SC)-based cell equalizers include (1) conventional SC, (2) single SC, (3) double-tiered SC, (4) modularized SC, (5) chain structure, (6) coupling SC, and (7) series-parallel SC. On the other hand, the resonant SC-based cell equalizers include (1) resonant SC, (2) conventional resonant type, (3) quasi-resonant type, (4) modularized type, and (5) chain type. First, the multi-winding transformer-based cell equalizer can be configured as either the flyback topology in Figure 9.12(a) or the forward topology. Second, in Figure 9.12(b), the buck/boost converter serves to deliver the surplus energy rapidly from the high-voltage cells to the low-voltage cells through a direct-current (DC) bus. Third, in Figure 9.12(c), to equalize the n cells, n–1 quasi-resonant converters are required, where 2n switches are populated. The resonant converters can balance the energy among the cells while maintaining the soft-switching operation. Fourth, in Figure 9.12(d), the inductor-based equalizer using a chain structure can increase the speed of cell balancing. However, its switching loss increases because of adding switches, and the voltage stress and current stress of capacitors may rise with the increasing number of cells. Besides the hardware parts, the software parts including the microcontrollers and algorithms are also very important for achieving the cell balancing reliably.

9.5.3 Fault Diagnosis and Prognostic

There are numerous types of faults related to power batteries, including (1) internal or external short-circuit fault, (2) over-charge or over-discharge fault, (3) BTMS fault, (4) sensor fault, and (5) actuator fault [34]. Accordingly, the functions of fault diagnosis and prognostic are significant to troubleshoot various battery faults in the applications of EVs and HEVs. Otherwise, some catastrophic accidents might happen, which may cause a severe threat to our personal and property safety. To identify the types of various faults, Figure 9.13 shows the categories of fault diagnosis and prognostic for EV batteries [26, 40], mainly including (1) distributed methods, (2) centralized methods, and (3) joint methods. Wherein, the distributed methods can be further classified into two branches, namely quantitative analysis methods and qualitative analysis methods. The qualitative analysis methods have the advantage of high interpretability but suffer from the failed applicability of complex systems and overreliance on the representativeness and integrity of knowledge [40]. Besides, the model-based methods can diagnose the faults accurately. The data-driven methods can be classified into three main types: (1) signal processing method, (2) machine learning method, and (3) information fusion method [41]. For the fault prognostic, the data-driven method offers an impressive accuracy by using the experiment data of a few early cycles only. Also, the data-driven method can present good reliability and robustness to disturbances.

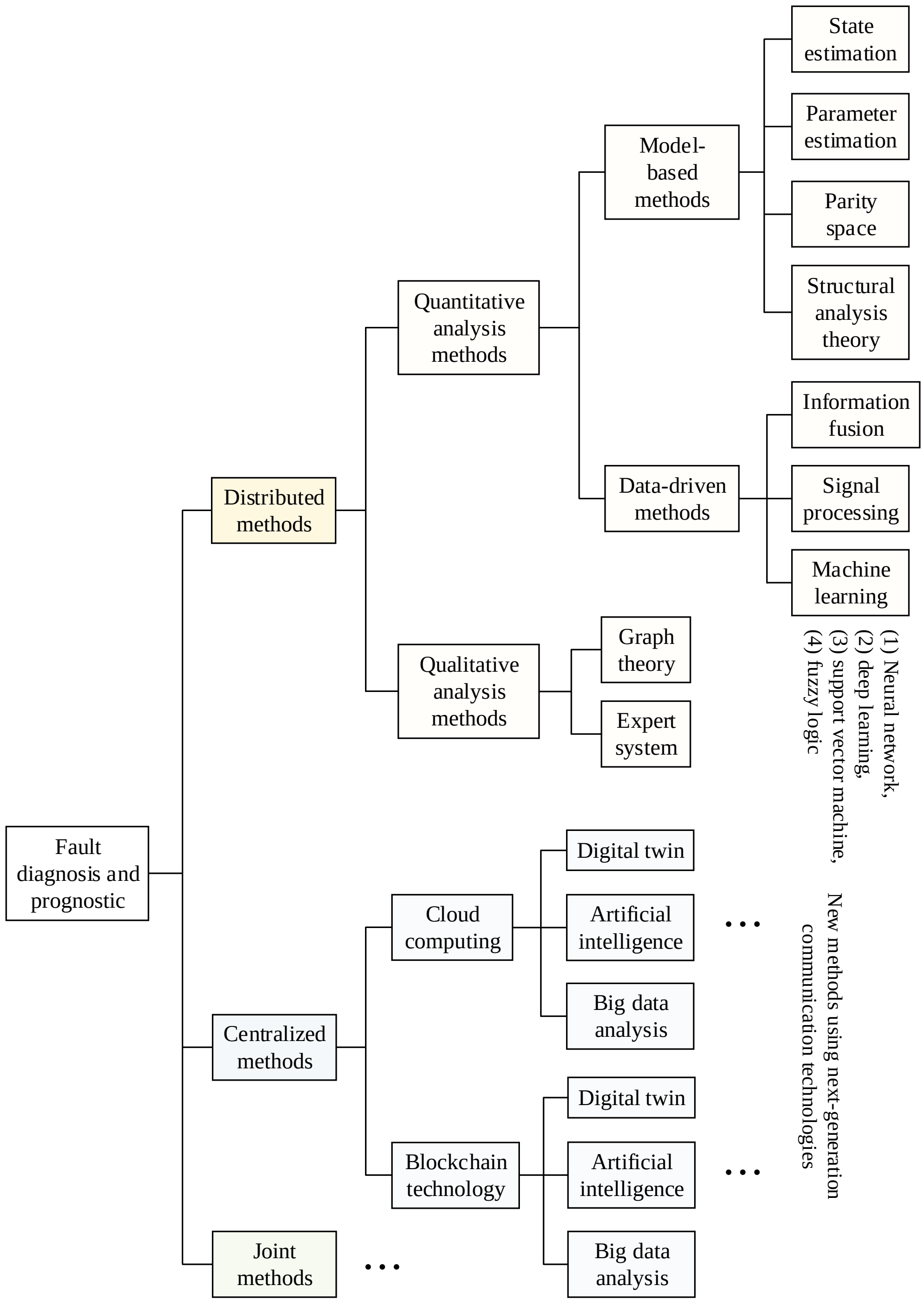

Figure 9.13 Categories of fault diagnosis and prognostic for electric vehicle batteries.

For the centralized methods, cloud computing and blockchain technology can be developed to realize the online fault diagnosis and prognostic for regional EV networks. Accordingly, cloud computing is to satisfy the computational requirements [42] with the help of modern communication technologies. In such a way, three emerging technologies of the digital twin, artificial intelligence, and big data analysis (or data mining) can be applied to build a fault diagnosis and prognostic system for large-scale EVs and HEVs equipped with batteries. Finally, the joint methods will build a strong collaboration with the distributed and centralized methods, thus integrating their advantages to compensate for each other. As a result, they will help establish a local and regional network to diagnose and prognose various faults in real time.

9.6 Emerging Management Technologies

In recent years, new battery management technologies emerge for achieving the functions of battery state estimation, thermal management, fault diagnosis, and health prognostic. Typically, some representative technologies will be discussed as follows, including (1) multi-model co-estimation, (2) artificial intelligence technology, (3) cloud computing technology, and (4) blockchain technology. Benefiting from the fifth-generation communication and next generations, the rapid development of these emerging technologies will further advance the smart battery management in turn.

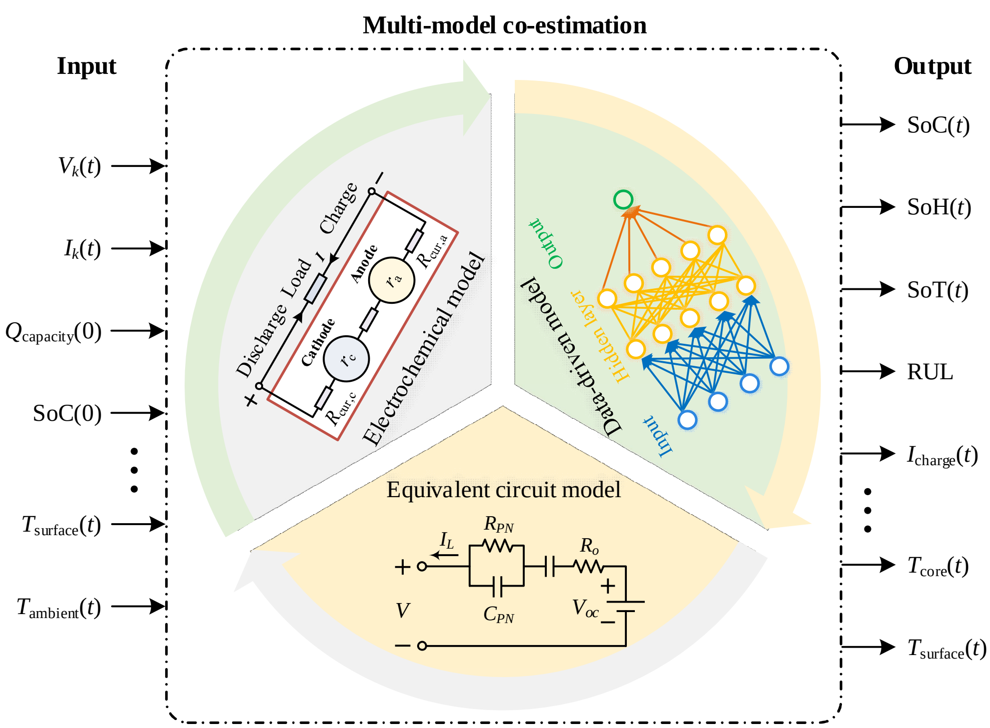

Figure 9.14 Multi-model co-estimation for battery management.

9.6.1 Multi-Model Co-Estimation

For improving the accuracy and robustness of battery state estimation, Figure 9.14 shows the multi-model co-estimation methods for battery management, which involve multiple models to perform the joint estimation [43, 44]. For example, in Figure 9.14, the electrochemical model, ECM, and data-driven model can be promisingly used to present a high-fidelity battery model, thus integrating the strengths of each method. Besides, the advanced microcontrollers allow the battery models to be more complex than ever before with higher accuracy and faster estimation speed.

Multi-mode co-estimation methods have drawn many researchers' attention focusing on improving the performance of battery management. Accordingly, two concepts of fusion estimation [44] and joint estimation [31] have been developed and verified for effective battery state prediction, such as for the SoC, SoT, SoH, or SoP. For example, multiple algorithms, such as linear regression, random forest, and support vector regression, can be fused readily for estimating the SoC [45]. Besides, to conduct the real-time multi-state joint estimation for EV batteries, a data-driven method can flexibly collaborate with other methods, such as the model-based unscented particle filter and support vector machine, for advancing the battery management performance.

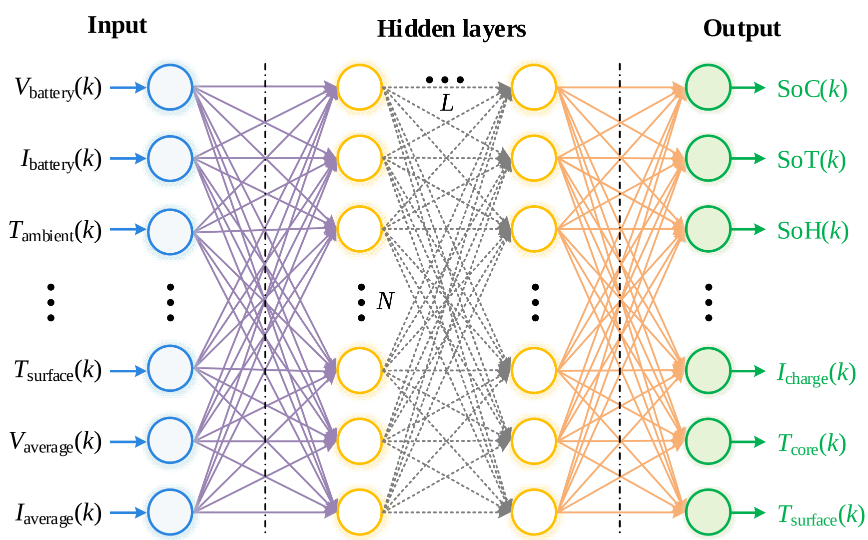

Figure 9.15 Neural network model for battery management.

9.6.2 Artificial Intelligence

The artificial intelligence technology has been well developed for various applications in recent decades. The battery management technologies have actively embraced the artificial intelligent methods. Focusing on this field, some artificial intelligent methods have attracted increasing attention and have been explored widely, including the machine learning methods, recurrent neural networks, and support vector machines [46, 47]. To implement the intelligent methods, huge data should be acquired by using various sensors and Internet-of-Thing devices in advance. Subsequently, these data will be further processed to train the artificial intelligence algorithms and extract the key features. Finally, a digital embodiment can be established for modeling the EV batteries accurately. Accordingly, Figure 9.15 shows a deep neural network algorithm for EV battery management [48], where the battery voltages, currents, surface temperature, and ambient temperature are all required as the inputs, while the targeted battery states (such as the SoC, SoC, and SoH), RUL, and core temperature can be predicted as the outputs.

The application of artificial intelligence enables the upgradation of smart BMS.

Typically, the digital twin technology may be used to develop a battery-information twin for intelligent battery management [49]. Relevant studies have been initiated and achieved rich outcomes. For example, by using an artificial neural network model, the SoH of LIBs was predicted precisely in a passive BTMS against different operating conditions [24]. Nevertheless, artificial intelligence also brings new challenges in interdisciplinary fields, such as data sensing, data computing, and data security, and hence continuous breakthroughs are still expected in these relevant fields.

9.6.3 Cloud Computing

To manage the batteries well for a large-scale EV network, the cloud computing technology can be appointed as a superior manager who can analyze and process the data and make the optimal decisions and predictions. Figure 9.16 shows the schematic of cloud computing technology incorporating artificial intelligence methods for regional battery management. The whole management system mainly consists of three parts, including (1) EVs and HEVs, (2) communication technology, and (3) cloud framework [50]. Moreover, the process of vehicular cloud computing networks can be derived into four steps: (1) Battery data acquisition, (2) data communication, (3) artificial intelligence, and (4) battery model. A local server is in charge of gathering the vehicular battery data and uploading the data to a cloud computing center, where intelligent algorithms can be applied to further data processing [51]. At the cloud computing center rather than an onboard BMS and a local server, both the data mining and big data analysis can be readily performed to handle such a huge dataset.

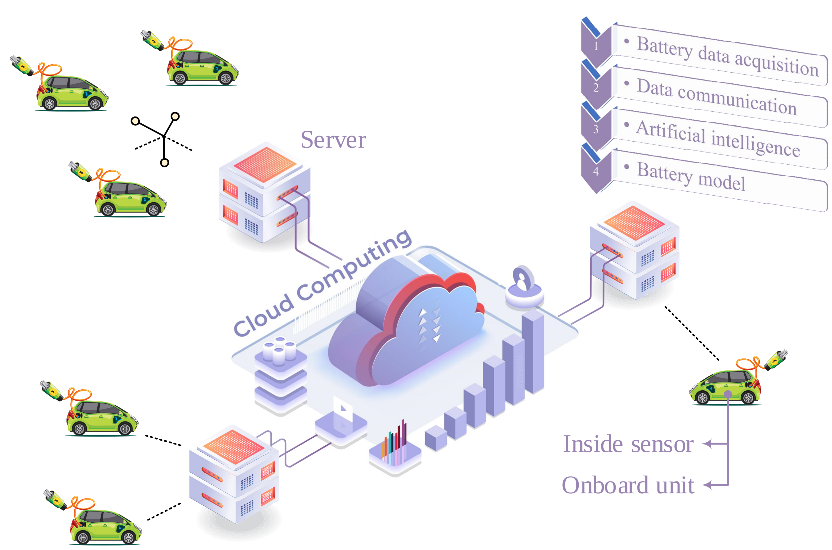

Figure 9.16 Cloud computing technology using artificial intelligence for regional battery management.

The rapid development of communication network technologies, such as the fifth-generation technology, sixth-generation technology, and next generations, can be quite competent for the data transmitting and receiving. Consequently, a vehicular

Internet-of-Thing can be networking for real-time data sharing and computing power sharing. Moreover, the cloud battery management center is capable of battery state estimation, fault diagnosis, and health prognostic, especially taking into account the aging effects on capacity and power fades [52]. Finally, the cloud BMS will deliver the computing results and recommendations to the local BMSs, namely local servers and onboard BMSs. Regional battery management can be completed successfully by remote monitoring and control.

9.6.4 Blockchain Technology

Figure 9.17 shows a scheme of blockchain technology, which serves for the battery management of EVs and HEVs. This blockchain technology has a typical two-layer hierarchy that includes one consortium blockchain and multiple private blockchains. With the help of advanced communication technologies, vehicular battery data can be shared in a league of multiple regions. Significantly, blockchain technology can ensure the data security and integrity, thus outperforming other technologies. On the one hand, each private blockchain is capable of recording both the encrypted data and public data, which are originated from every EV and HEV. On the other hand, the consortium blockchain is in charge of collecting both the public indexes and secure indexes, which are researchable and generated from the public data and encrypted data, respectively [50]. Furthermore, various malicious cyber-physical attacks can be blocked to protect the Internet-connected BMSs. This blockchain technology can offer intelligent monitoring, prognostic, and control [53] for precise battery management in a regional EV league [54]. Having privacy protection for stakeholders, this blockchain technology enables anonymous transactions among EVs and energy routers, which may serve the battery management and power distribution in a virtual EV power network [55].

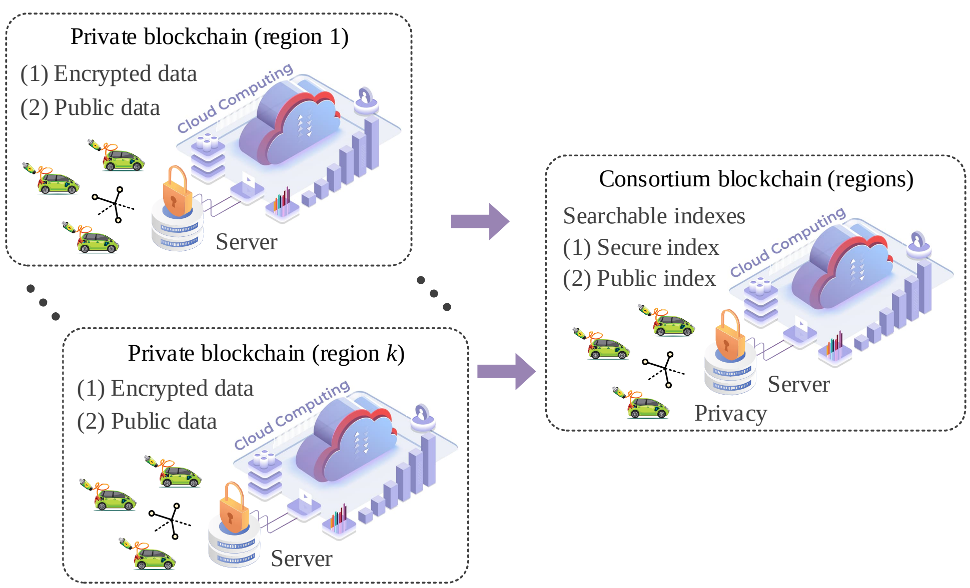

Figure 9.17 Blockchain technology of regional battery management for hybrid and electric vehicles.

Finally, a VIEI is envisioned for energy and data sharing in Figure 9.18, which can help relieve the overdependence on batteries and onboard BMSs in a network of EVs and HEVs. Accordingly, the blueprint of VIEI contains six parts: (1) Vehicular power network [56, 57], (2) energy internet and router [55], (3) artificial intelligence, (4) vehicle-to-grid, (5) vehicle-to-home, and (6) vehicle-to-vehicle. In the regime of VIEI, effective sharing of vehicular data and computing power may collaborate with the autonomous driving, hence advancing the electrified transportation [58]. Moreover, the multi-internet merging will embrace the vehicular Internet of Things [59, 60], thus enabling new functions and widening the scales of information, energy, and humanity internets. Thanks to the assistance of artificial intelligence and cloud computing technologies, both the EVs and HEVs will provide more types of service, more than pure transportation tools. To block malicious attackers, the emerging technologies, such as data-driven artificial intelligence and blockchain technology, will be applied to guarantee both the security and privacy of data and energy [61], therefore benefiting the achievement of a smarter VIEI.

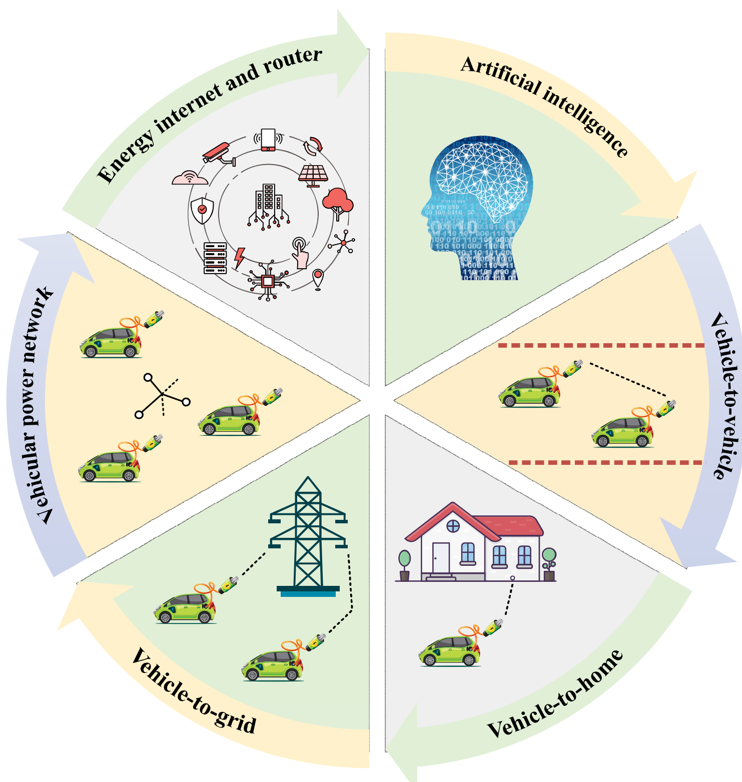

Figure 9.18 Blueprint of vehicular information and energy internet.

9.7 Conclusion

This chapter analyzed and discussed the state-of-the-art technologies of battery management in HEVs and pure EVs thoroughly. Various advanced and emerging methods were introduced for battery modeling, battery state estimation, safety prognostic, and fault diagnosis. Meanwhile, their main features, advantages, and disadvantages were also presented. Significantly, the data-driven method can be identified as a promising technology for developing a dynamic data-driven electrothermal model, which may offer accurate state estimation and reliable health prognostic by using a dataset of fewer early cycles only. Finally, with the help of communication technologies and intelligent management methods, a blueprint of VIEI was envisioned to support the vehicular data and energy sharing and smarter battery management for a network of HEVs and EVs.

Acknowledgment

This work was fully supported by a grant (Project no. T23-701/20-R) from the Hong Kong Research Grants Council, Hong Kong Special Administrative Region, China.

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