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Review

A review on the key issues for lithium-ion battery management in electric vehicles

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HIGHLIGHTS

- ► This paper briefly reviews key technology of battery management system in EV.
- ► The composition of battery management system is analyzed.
- ► The battery state estimation methods are summarized and compared.
- ► The battery uniformity theory and equalization methods are reviewed.
- ► The battery fault diagnosis methods are discussed.

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ABSTRACT

Compared with other commonly used batteries, lithium-ion batteries are featured by high energy density, high power density, long service life and environmental friendliness and thus have found wide application in the area of consumer electronics. However, lithium-ion batteries for vehicles have high capacity and large serial-parallel numbers, which, coupled with such problems as safety, durability, uniformity and cost, imposes limitations on the wide application of lithium-ion batteries in the vehicle. The narrow area in which lithium-ion batteries operate with safety and reliability necessitates the effective control and management of battery management system. This present paper, through the analysis of literature and in combination with our practical experience, gives a brief introduction to the composition of the battery management system (BMS) and its key issues such as battery cell voltage measurement, battery states estimation, battery uniformity and equalization, battery fault diagnosis and so on, in the hope of providing some inspirations to the design and research of the battery management system.

1. Introduction

Compared with other commonly used batteries, lithium-ion batteries are featured by high energy density, high power density, long life and environmental friendliness and thus have found wide application in the area of consumer electronics. However, automotive lithium-ion batteries have high capacity and large serial-parallel numbers, which, coupled with such problems as safety, durability, uniformity and cost, imposes limitations on the wide application of lithium-ion batteries in the vehicle. Lithium-ion batteries must operate within the safe and reliable operating area, which is restricted by temperature and voltage windows. Exceeding the restrictions of these windows will lead to rapid attenuation of battery performance and even result in safety problem. According to the instructions of most battery manufacturers, the reliable operating temperatures required by a majority of current automotive lithium-ion batteries (graphite/$LiMn_2O_4$ or by acronyms C/LMO, C/$LiCo_xNi_yMn_zO_2$ or C/NCM, C/$LiFePO_4$ or C/LFP, C/$LiNi_{0.8}Co_{0.15}Al_{0.05}O_2$ or C/NCA) are: discharging at −20 to 55 °C and charging at 0–45 °C and for lithium-ion battery with $Li_4Ti_5O_{12}$ or LTO negative electrode, the minimum charge temperature can be −30 °C. Usually, the operating voltage of lithium-ion batteries is between 1.5 V and 4.2 V (C/LCO, C/NCA, C/NCM and C/LMO about 2.5–4.2 V, LTO/LMO about 1.5–2.7 V and C/LFP about 2.0–3.7 V). As indicated in Fig. 1, normally when the temperature is 90–120 °C, the SEI film will start exothermic decomposition [1–3],

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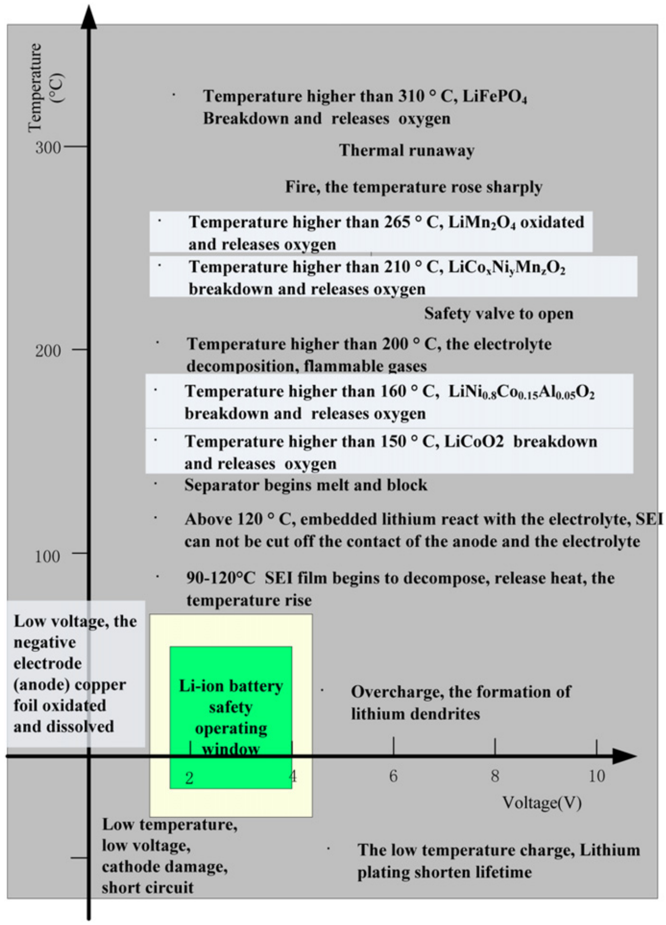


Fig. 1. Safety operating window for lithium ion battery (modified from [11]).

but some electrolyte systems will decompose at a lower temperature of about 69 °C [4]. When the temperature exceeds 120 °C, the SEI film after decomposition is unable to protect negative carbon electrode from side reactions with the organic electrolyte and combustible gas would be produced [3]. When the temperature is about 130 °C, the separator will start melting and shutting the cell down [5,6]. When the temperature becomes higher, the positive material will start decomposition ($LiCoO_2$ will start decomposition at temperature of about 150 °C [7], $LiNi_{0.8}Co_{0.15}Al_{0.05}O_2$ at about 160 °C [8,9], $LiNi_xCo_yMn_zO_2$ at about 210 °C [8], $LiMn_2O_4$ at about 265 °C [1] and $LiFePO_4$ at about 310 °C [7]) and produce oxygen. When the temperature is above 200 °C, the electrolyte will decompose and produce combustible gas [3], and it will have violent reaction with the oxygen produced by the decomposition of the positive electrode [9] and start to catch fire and lead to thermal runaway. To charge lithium-ion batteries below 0 °C will lead the metallic lithium to deposit on the carbon negative electrode surface and therefore reduce the cycle life of batteries [10]. At an extremely low temperature, the cathode of batteries will break down, and result in short circuit [11]. If the voltage is too low or the batteries are overdischarged, the phase change will lead the lattice to collapse and therefore the performance of the batteries is influenced [12]. Moreover, it will lead the negative copper collector to dissolve in the electrolyte (For this reaction, the thermodynamic equilibrium potential is 0.521 V vs. SHE (Standard Hydrogen Electrode) or 3.566 V vs. Li/Li+ under standard condition). When the batteries are recharged, the copper dendrite will be formed at the negative electrode, which, consequently, will result in short circuits within the batteries [1,12]. An extremely low voltage or overdischarge will also lead to the reduction of the electrolyte, produce combustible gas [12] and therefore pose potential security risks. An extremely high voltage or overcharge will lead the positive electrode to compose and therefore a great amount of heat is produced [12,13]. It will also lead the metallic lithium to be deposited on the surface of negative electrode, which will accelerate the capacity fade, result in internal short circuits and safety problem [12], as well as the decomposition of the electrolyte (the common electrolyte will decompose if the voltage is higher than 4.5 V [12]). To solve those problems, people try to develop new battery system that could be working under very bad situations, and on the other hand, the current commercial lithium-ion batteries must be fitted with a management system, through which the lithium-ion batteries can be controlled and managed effectively, thus every single cell would be working under proper conditions that those fault described above would not happen which means that every cell should be operated within the lithium-ion battery safety operating window shown in Fig. 1. This present paper, through the analysis of literature and in combination with our practical experience, gives a brief introduction to the composition of the BMS and its key issues, including such issues as battery cell voltage measurement, battery states estimation, battery uniformity and equalization, battery fault diagnosis and so on, in the hope of providing some inspirations to the design and research of the battery management system.

2. Status of lithium-ion battery and battery management system (BMS) in EV

Many kinds of lithium-ion batteries are employed in electric vehicle (EV). The most widely used power battery cells contain carbon anode (negative electrodes), and now the LTO anode is also developed fast for these kind of anodes would help to improve the battery durability and performance of fast charging. The positive electrode material of the power battery could be LMO, LFP, NCM, NCA, etc. Some of the current EV and the employed batteries are listed in Table 1 [14–22].

Usually, the capacity and voltage of the battery cell used in the EV are relatively small. So first the single battery cells should be packed and integrated to a battery module, and the battery system in the EV often contains one or more module according to the requirement. The battery system usually consists of hundreds or thousands of single cells. To manage so many cells, the battery management system (BMS) is very important.

There is still no consensus of the final definition of BMS and what BMS do. According to Ref. [23,24], we adopt the wide view that BMS is any system that manages the battery. The system could be electronic systems, mechanical systems or any possible device and technology. The battery could be a single cell, battery module or battery pack, and it could be rechargeable or non-rechargeable.

Table 1
Some current EV and the employed lithium-ion batteries.

Vehicle	Battery supplier	Positive electrode	Negative electrode
Nissian Leaf EV	Automotive Energy Supply (Nissan NEC JV)	LMO	C
Chevrolet Volt	Compact Power (subsidiary of LG Chem)	LMO	C
Renault Fluence	Automotive Energy Supply (Nissan NEC JV)	LMO	C
Tesla Roadster		NCA	C
Tesla Model S	Panasonic Energy	Nickel-type	
BYD E6	BYD	LFP	C
Subaru G4e	Subaru	LVP	C
Honda Fit EV	Toshiba Corporation	NCM	LTO

The system could manage the battery by monitoring the battery, estimating the battery state, protecting the battery, reporting the data, balancing it, etc.

BMS in vehicles is comprised of kinds of sensors, actuators, controllers which have various algorithms and signal wires. Three main tasks of the BMS in vehicles are as follows [25].

- To protect the cells and battery packs from being damaged.
- To make the batteries operate within the proper voltage and temperature interval, guarantee the safety and prolong their service life as long as possible.
- To maintain the batteries to operate in a state that the batteries could fulfill the vehicles' requirements.

And the automotive power batteries must also meet relevant standards or specifications [26–32].

The basic framework of hardware from BMS in vehicle is shown in Fig. 2.

The BMS would have inputs such as: main circuit current sensor and voltage sensor to measure the main current and voltage; temperature sensors to measure the temperature of the cells, the temperature outside the battery box, and maybe also the temperature at the battery coolant inlet and outlet; general analog inputs like accelerate pedal sensor and brake pedal sensor; and general digital inputs like Start key ON/OFF signals, charging allow/banned switch, etc.

The BMS would have outputs such as: thermal management module like fan and electric heater to do the cooling control and heating control; balancing module like capacitor + switch array and dissipation resistance to do the battery equalization; voltage safety management like main circuit contactor, battery module contactor; general digital outputs like charging indicator, failure alarm; and communication module. And also the BMS would have the internal power supply module and global clock module. And it may have the charging system and man–machine interface module. The electromagnetic compatibility should also be guaranteed. The bad working environment of electric motor cars requires BMS to possess good anti-electromagnetic interference capacity and send out low levels of radiation as well.

The software of BMS would cover these functions.

(1). Battery parameters detection

This includes total voltage, total current and individual cell voltage detection (to prevent overcharging, overdischarging and antipole), temperature detection, smoke detection, insulation detection, collision detection, impedance detection and so on.

(2). Estimation of battery states

This includes state of charge (SOC) or depth of discharge (DOD), state of health (SOH) and state of function (SOF). SOC or DOD of batteries is estimated according to such conditions as working current, temperature and voltage. SOH is estimated according to the extent of abuse and performance degradation of batteries. SOF is estimated according to SOC, SOH and operating environment of batteries.

(3). On-board diagnosis (OBD)

The faults include sensor fault, actuator fault, network fault, battery fault, overvoltage (overcharge), undervoltage (overdischarge), overcurrent, ultra high temperature, ultra low temperature, loose connection, exceeding combustible gas concentration, insulation fault, uniformity fault, over-fast temperature rise and so on.

(4). Battery safety control and alarm

This includes thermal system control and high voltage safety control. When the faults are diagnosed, the vehicle control unit or the charger will be informed through the network and they are required to handle the faults (when a certain threshold value is exceeded, BMS can also cut-off the battery power supply) to prevent damage to batteries or injuries to people caused by high temperature, low temperature, overcharge, overdischarge, overcurrent, electric leakage and so on.

(5). Charge control

On the basis of the properties of its own batteries and the power level of the charger, BMS could control the charger to charge the batteries.

(6). Battery equalization

According to the information of each cell, BMS adopts such equalization methods as equalizing charging, dissipative equalization or non-dissipative equalization to make the SOC between cells as consistent as possible.

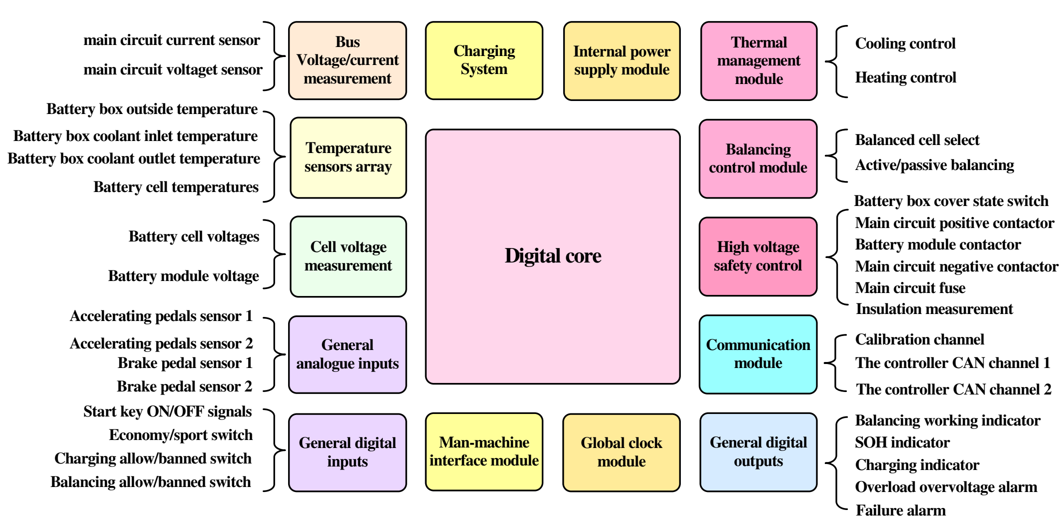


Fig. 2. Basic framework of software and hardware of BMS in vehicle.

(7). Thermal management

According to the temperature distribution within the battery pack and the requirements of charge or discharge, BMS decides whether to start heating or cooling as well as heating power and cooling power.

(8). Networking

Since it is not convenient to disassemble BMS in a vehicle and meantime the vehicle is required to have network functions, it is desirable to conduct on-line calibrating and monitoring, automatic code generation and on-line program downloading (program update without disassembling the case) for BMS without disassembling the case. Usually the network CAN (Controller Area Network) is adopted.

(9). Information storage

BMS is used to store key data, such as SOC, SOH, accumulated charge and discharge Ah numbers, fault code, uniformity and so on.

The real BMS in the vehicle may only have parts of the hardware and software which is mentioned above. There should be at least one cell voltage sensor and one temperature sensor for each battery cell. For a battery system with only scores of cells, there may be only one BMS controller or even the BMS function would be integrated in the main controller of the vehicle. And for the battery system with hundreds of cells, there may be one master controller and several slave controllers which only manage one battery module. For each battery module with dozens of cells, there could be some module circuit contactor and balancing module, and the slave controller would manage the battery module like measuring the voltage and current, controlling the contactor, equalizing the cells and communicating with the master controller. The master controller would do the battery state estimation, fault diagnosis, thermal management, etc. according to the data reported by the slave controllers.

Nowadays, BMS has become a focus that is developed by various vehicle companies, colleges and universities [33–39]. Currently, quite a few companies have developed corresponding BMS products, such as the products developed by Beijing Key Power Technology Co., Ltd [40], Harbin Guantuo Power Equipment Co. Ltd [41], Anhui Ligoo New Energy Technology Co. Ltd [42], Huizhou Epower Electronic Co. Ltd [43], American Elithion Corporation [44], Australian EV power [45] and British REAPSystems [46], etc.

3. Key issues of BMS

Although BMS has many functional modules, this present paper only analyzes and summarizes its key issues. At present, the key issues or difficulties of BMS are precise measurement of cell voltage, estimation of battery states, battery uniformity and equalization, and battery fault diagnosis.

3.1. Cell voltage measurement (CVM)

The major difficulties of CVM lie in: (1) the battery packs of electric motor cars have hundreds of cells connected in series and thus there are many channels to measure the voltage. As there is accumulated potential when the cell voltage is measured and the accumulated potential of each cell is different from that of another, which makes it impossible to have unified compensation or elimination methods, certain difficulties arise in the design of circuit measurement. (2) Voltage measurement requires high precision (especially for C/$LiFePO_4$ battery). Estimation of SOC and other battery states imposes high requirements on cell voltage precision. Here we take the C/LFP and LTO/NCM type batteries as example. Fig. 3 shows the open circuit voltage (OCV) of batteries C/$LiFePO_4$ and LTO/NCM as well as corresponding SOC variation per mV voltage. From this figure, we can find that the slope of OCV curve of LTO/NCM is relatively steep and the maximal corresponding SOC rate of change per mV voltage is lower than 0.4% in most range (except SOC 60–70%). Therefore, if the measurement precision of cell voltage is 10 mV, then the SOC error obtained through OCV estimation method is lower than 4%. Accordingly, for LTO/NCM battery, the measurement precision of cell voltage needs to be smaller than 10 mV. But the slope of OCV curve of C/$LiFePO_4$ is relatively gentle and the maximal corresponding SOC rate of change per mV voltage reaches 4% in most range (except SOC <40% and 65–80%). Therefore, the collection precision of cell voltage has a high requirement, reaching around 1 mV. At present, most collection precision of cell voltage reaches only 5 mV.

In literature [47] and [48] the voltage measurement methods of batteries cells and fuel cells stacks are, respectively, summarized. The methods include resistance voltage divider method, optical coupling isolation amplifier method, discrete transistor method [49], distributed measurement method [50], optical coupling relay method [51], and so on. Currently, the voltage and temperature sampling of cells has formed chip industrialization and Table 2 compares the performance of chips used in most BMS.

3.2. Battery states estimation

Battery states include SOC, SOH and SOF and their relationship is shown in Fig. 4. SOH is determined by service life prediction and fault diagnosis output together. SOF is determined by SOC, SOH and the fault states. SOF takes into consideration the influence of aging factor, SOC range, temperature range and fault level.

3.2.1. SOC estimation algorithm

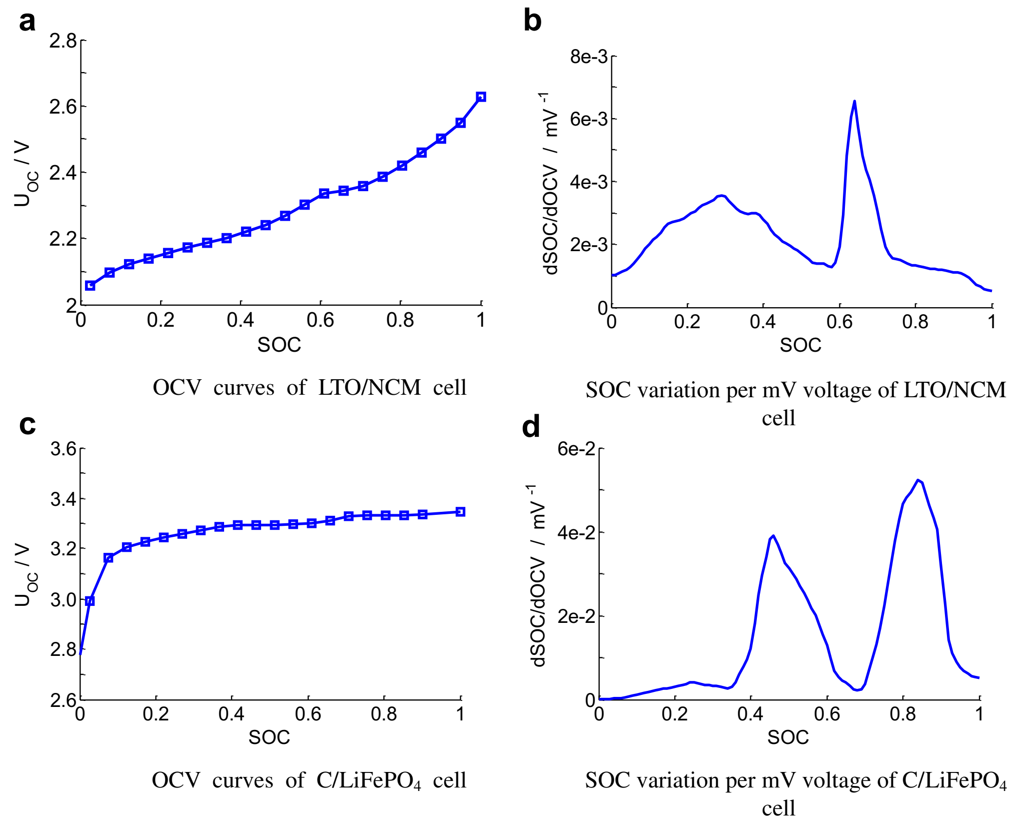
There is not a final generally accepted definition of SOC. Here we take this view that the state of charge (SOC) means the ratio of the remaining charge of the battery and the total charge while the battery is fully charged at the same specific standard condition [52]. And the SOC is often expressed in percent, 100% means fully charged and 0%means fully discharged.

There is no doubt of this definition for a single battery cell, but for the battery module (or a battery pack, since the battery pack is consisted of several modules, so to calculate the SOC of the battery pack from the SOC of the battery modules is just like the way to find the SOC of the battery module from the SOC of the single cells. It is the same for the other states variables), the situation is a bit complicated. Battery module which is connected by several cells in parallel could be considered as a single cell with high capacity and the SOC could be just estimated just like the single cell, since the self-balancing characteristic of the parallel connection.

Though under the series connection condition, the SOC of the battery module could also be estimated just like the single cell, but consider the battery uniformity, it would be better to considered in detail. Assume that the capacity and SOC of each single cell in the battery module are known. If there is a very efficiency and non-lossy balancing device, then the SOC of the battery module is:

$$\mathrm{SOC_M} = \frac{\sum \mathrm{SOC}_i C_i}{\sum C_i} \quad (1)$$

where SOC_M means the SOC of the battery module, the SOC_i means the SOC of the ith battery cell and the C_i means the capacity of the ith battery cell. If the balancing device is not so efficiency, the real



OCV curves of LTO/NCM cell

SOC variation per mV voltage of LTO/NCM cell

OCV curves of C/$LiFePO_4$ cell

SOC variation per mV voltage of C/$LiFePO_4$ cell

Fig. 3. OCV curves and the SOC variation per mV voltage (measured under 25 °C, and rest time 3 h).

SOC of the battery module is related to the real performance of this balancing device.

If there is no balancing device or with dissipation balancing device, there would be some waste capacity which could not be used like shown in Fig. 5 while there exists variations between the cells in the battery module.

Thus, the capacity of the battery module is:

$$C = \min(SOC_iC_i) + \min((1 - SOC_i)C_i) \quad (2)$$

And the remaining available capacity of the battery module is:

$$C_R = \min(SOC_iC_i) \quad (3)$$

Thus, the SOC of the battery module is:

$$SOC_M = \frac{\min(SOC_iC_i)}{\min(SOC_iC_i) + \min((1 - SOC_i)C_i)} \quad (4)$$

Anyway, with the precise estimation of the cell SOC and the uniformity of the battery modules, the SOC of the module could be calculated. The most challenging work is how to estimate the cell SOC for the BMS in the vehicles.

There are many methods to estimate the SOC in electrical chemistry laboratory like coulometric titration technique [53]. But it is quite challenging to estimate the SOC of commercial batteries without destruction of the battery or interruption of the battery power supply, especially the on-line estimation in vehicle. Currently there has been intensive study on SOC estimation algorithm would be introduced as follows.

(1) Discharge test method

The most reliable method to determine the battery SOC is the discharge test with controlled conditions, i.e., specified discharge

Table 2
Statistics of battery management and equalization chips.

Company and product name	Analog Devices Co. AD7802	Linear Technology Co. LTC6802	Texas Instrument Co. bq76PL536	Atmel Co. ATA6870	Maxim Co. MAX11068
Voltage measurement channels	6	12	6	6	12
Temperature measurement channels	6	2	2	2	2
Max chips in daisy chain	20	36	>16	16	31
Max cells in serial	120	432	>96	96	372
Max voltage of daisy chain (V)	380	>1000	N/A	N/A	N/A
AD resolution (Bit)	12	12	14	12	12
AD conversion time	1μs	1.08ms	6μs	N/A	10μs
Equalization	Yes	Yes	Yes	Yes	Yes
Operating temperature range (°C)	−40 to 105	−40 to 85	−40 to 85	−40 to 85	−40 to 105
Standby current (μA)	4	60	12	10	1
Input voltage range (V)	7.5–30	10–50	6–36	6–30	6–70

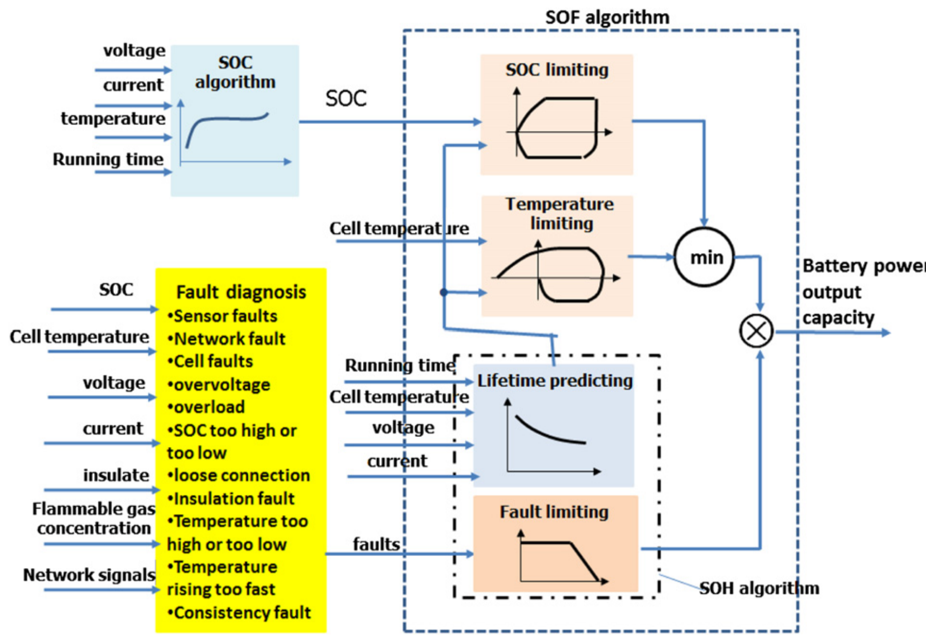


Fig. 4. BMS state estimation algorithm framework.

rate and ambient temperature. This test could precisely find the remaining charge of the battery then the SOC, but the consumed time is pretty long and after the test the battery would have no power, thus this method could be only used in laboratory but not useful for BMS to do the on-line estimation of batteries in vehicle.

(2) Ampere-Hour integral (coulomb counting) method

This method is the most simple and general method to get the battery SOC. The Ampere-Hour integral method could be represented by Eq. (5),

$$\mathrm{SOC} = \mathrm{SOC}_0 - \frac{1}{C_N}\int_{t_0}^{t} \eta I \cdot \mathrm{d}\tau \tag{5}$$

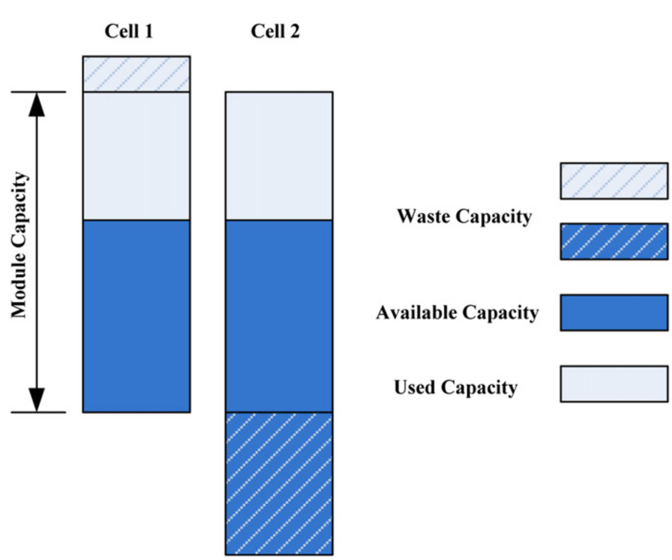


Fig. 5. The waste capacity and remaining capacity of a battery module (take a battery module of 2 cells as example).

where SOC_0 represents SOC at the initial time t_0; C_N represents rated capacity (the capacity of the battery in standard condition, changing with service life); η represents coulombic efficiency which is equal to 1 while discharging and is smaller than 1 while charging; I represents current which is negative at charge and positive at discharge.

The results of Ampere-Hour integral method have quite satisfactory precision within a certain period of time (it is mainly related to the sampling precision and frequency of the current sensor) if the initial SOC_0 is relatively precise. Nevertheless, it has the following disadvantages: (i) the initial SOC_0 precision influences on the precision of SOC, and Ampere-Hour integral method cannot get the precise initial SOC_0 automatically; (ii) the Coulombic efficiency can be greatly influenced by the operating states of batteries (such as SOC [54,55], temperature, current, etc.), which is difficult to measure precisely and then produces cumulative effects on SOC error; and (iii) the precision of the current sensor, especially the measurement drift will result in cumulative effects and then influence the precision of SOC. Therefore, the SOC estimation results of only using the Ampere-Hour integral method cannot meet the requirement of SOC precision.

(3) Open circuit voltage method

SOC is related to the embedding quantity of lithium-ion in the active material and with static thermodynamics. Therefore, the open circuit voltage after adequate resting which can be considered to reach balanced potential, since there is a one-to-one correspondence between OCV and SOC and bear little relation to the service life of batteries, is an effective method to estimate SOC of lithium-ion batteries [56–59].

The greatest advantage of the open circuit voltage method is the high precision of SOC estimation while its remarkable disadvantage is that batteries are required to have long time resting in order to reach balance. It usually takes some time for batteries to recover from an operating state to a balanced state and the time duration is related to the states of SOC, temperature, and so on [60,61]. It takes $C/LiFePO_4$ battery more than three hours at low temperature [60]. Therefore, this method, if used alone, is suitable only when electric vehicles are parking rather than driving.

And careful consideration and research are needed as the open circuit voltage of some kinds of batteries is related to the charge/discharge process (history). For example, the charge open circuit voltage and discharge open circuit voltage of C/$LiFePO_4$ batteries have hysteretic phenomena (similar to the Ni-MH battery) [62–65,60], as indicated in Fig. 6. Gerschler et al. introduce some detailed interesting experiments about hysteretic phenomena of different battery types including NCM, NCA and LFP types [66].

(4) Battery model-based SOC estimation method

The OCV method need enough rest time to estimate the SOC, thus it cannot be used while the vehicle is driving. So if we could on-line estimate the OCV during the driving, then the battery SOC could be easily derived. To on-line get the battery OCV, a battery model is needed.

The commonly used battery models include equivalent circuit model [67], and electrochemical model [68–70]. Usually a battery model, especially an ECM model, could be expressed as

$$U = U_{OC} - U_R - U_p \tag{6}$$

where U is the battery terminal voltage, U_{oc} is the battery OCV, U_R is the voltage drop caused by the ohmic resistance, U_p is the voltage drop caused by some internal polarization process. So it is easily to found the battery OCV if the battery model parameters are known. Then using the OCV-SOC look-up table derived by experiment, the battery SOC could be easily found. H.W. He, et al. [71] use this method and take the Rint model, first-order RC model and the second-order RC model, respectively, and find that using the second-order RC model the maximum estimation error is 4.3% and the mean error is 1.4%.

For this method, the precision and complexity of battery model are very important. Hua et al. [67] collected 12 commonly used equivalent circuit models, including the combined model, the Rint model (simple model), the Rint model with the zero-state hysteresis model, the Rint model with the one-state hysteresis model, the Enhanced Self-correcting (ESC) model with two-state low-pass filter, the ESC model with four-state low-pass filter, the first-order RC model, the first-order RC model with one-state hysteresis, the second-order RC model, the second-order RC model with one-state hysteresis, the third-order RC model and the third-order RC model

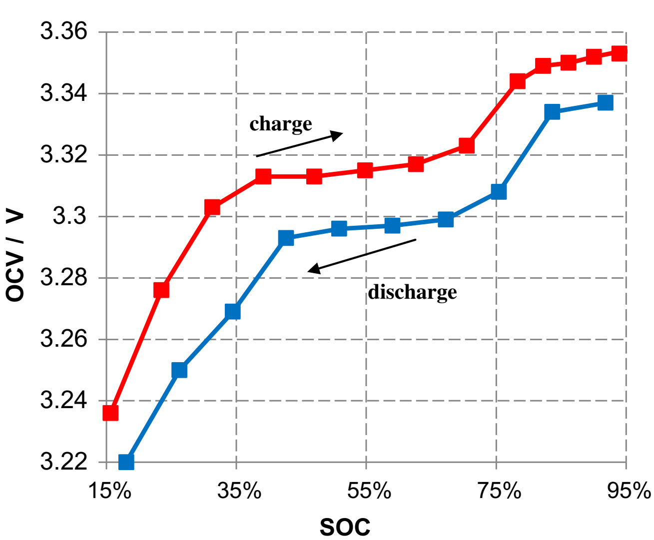


Fig. 6. Charge and discharge OCV curves of C/$LiFePO_4$ (measured under 25 °C, and rest time 3 h).

with one-state hysteresis. These models can be used for dynamic estimation, but the estimation precision is related to the model precision and the signal collection precision. Hua et al. [67] adopt experimental data, fit the parameters of the above twelve equivalent circuit models and compare the precision and complexity of the models. The research results show that the first-order RC model with one-state hysteresis, which is simple and have high precision, is more suitable for the voltage estimation of $LiFePO_4$ battery.

Electrochemical model is established on the basis of mass transfer, chemical thermodynamics and electrodynamics, and many parameters of batteries internal materials are involved which are hard to obtain with accuracy. Since the huge computations, this model is usually used for the battery performance analysis and battery design.

(5) Neural network model method

Neural network model method [72,73] estimates SOC through the use of nonlinear mapping characteristics of the neural network. When building a model, the neural network method does not have to take into consideration the details of batteries, and it boasts universality, suitable for the SOC estimation of all kinds of batteries. But a great number of training sample data are needed to train the network and the estimation errors can be greatly influenced by training data and training methods [73]. Meanwhile the neural network method requires a lot of computations, which necessitates powerful processing chips (such as DSP).

(6) Fuzzy logic method

The basic idea for the fuzzy logic method [74–77] is to simulate the fuzzy thinking of human beings by using the fuzzy logic on the basis of a great number of test curves, experience and reliable fuzzy logical theories and eventually to realize SOC prediction [77]. This method requires first enough understanding of the batteries themselves and meanwhile relatively large computations.

(7) Other SOC estimation methods based on battery performance

There are such methods as alternating current (AC) impedance method [78–80], direct current (DC) internal resistance method [81]. In the AC impedance method, a series of small amplitude sinusoidal alternating currents of different frequencies are loaded to the batteries and then measure the frequency response function of the battery system under different frequencies. SOC of batteries can be obtained through the analysis of AC impedance. One difference of the DC internal resistance method from the AC impedance method is that the former has fixed time interval to calculate the internal resistance of the batteries and the resistance can be ohm resistance (the time interval is short enough). The DC internal resistance bears certain relation to SOC of the batteries and such a relation can be a basis to obtain SOC of the batteries.

Due to the following reasons:

i. The use of the AC impedance method requires a signal generator [82], which will increase cost.
ii. The impedance spectroscopy or internal resistance of batteries has a complicated relationship with SOC and there are many influencing factors (including the uniformity of internal resistance).
iii. The internal resistance of batteries is very small and that of the batteries in vehicle is at the level of milliohm, which makes it difficult to obtain the internal resistance with accuracy.
iv. The internal resistance of lithium-ion batteries varies little in a wide range and is hard to recognize, as indicated in Fig. 7.

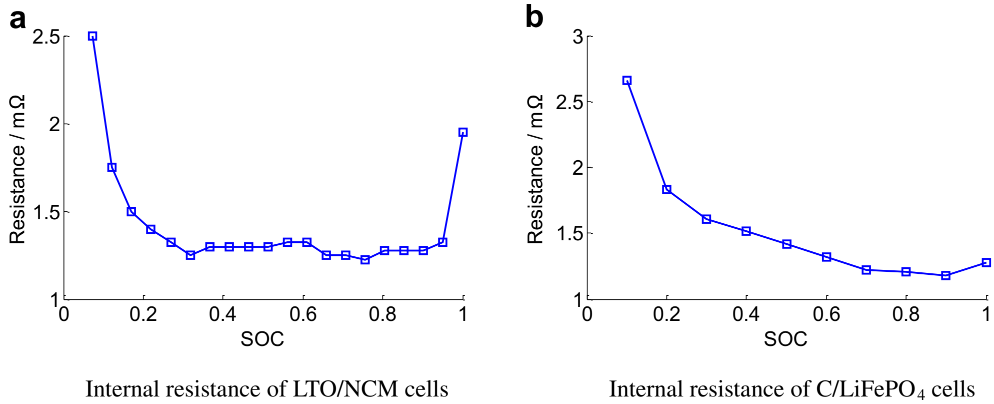


Fig. 7. Internal resistance of lithium ion batteries (measured under 25 °C, using the HPPC test procedure).

It is difficult for AC impedance method and DC internal resistance method to find direct application in battery SOC estimation in vehicle. Usually they are used in fault diagnosis.

(8) Integrated algorithm based on the two of more of the above methods

Currently the integrated methods include simple correction, weighted fusion algorithm, Kalman filtering (or Extended Kalman filtering, EKF), sliding mode observer and so on.

The simple correction integrated algorithm mainly includes Ampere-Hour integral method with correction by open circuit voltage, Ampere-Hour integral method with SOC calibration after full charging [55] and so on. For batteries in pure electric vehicles. (i) The working conditions are simple. When the vehicles are moving, except a little braking regeneration, the batteries are mainly in a discharge state; when the vehicles are charged in a charging station, their batteries are in a charge state. The hysteresis of the open circuit voltage is easy to estimate. (ii) The batteries have large capacities and the errors of the Ampere-Hour integral are relatively low. iii. The possibility to be fully charged is great. Therefore, Ampere-Hour integral method with the initial SOC correction according to the open circuit voltage and SOC calibration after full charging could meet the precision requirement of SOC estimation of batteries for pure electric vehicles. But for batteries in hybrid electric vehicles (HEV). (i) The working conditions are complex. When the vehicles are moving, the current are both charged and discharged in order to keep the battery SOC in a narrow range. (ii) Except from maintenance, there is no chance of full charging when the vehicles are parked. (iii) The batteries have small capacities and the errors of Ampere-Hour integral methods are relatively high. Therefore, the simple open circuit voltage correction method is unable to meet the requirements and other integrated methods are needed.

The weighted fusion algorithm is to add up the SOC estimated through different methods in accordance with certain weights to obtain SOC. Verbrugge et al. [83] adopt the weighted fusion algorithm using the SOC obtained through the Ampere-Hour integral and the SOC obtained through the first-order RC model with hysteresis, as shown in formula $\mathrm{SOC} = w(\mathrm{SOC_C}) + (1 - w)(\mathrm{SOC_V})$, where w represents the weight. This algorithm has been applied in the GM hybrid dynamic system and Fig. 8 shows the block diagram of this algorithm.

In the Kalman filtering algorithm, since SOC cannot be measured directly, two methods of SOC estimation are integrated as a dynamic system, in which the SOC is regarded as an internal state of the system and is analyzed. Furthermore, because the battery system is a nonlinear system, the EKF method is usually adopted. Generally, researches are conducted through systems formed by the Ampere-Hour integral method and other battery models. Gregory L. Plett [82] introduces five Kalman integrated algorithms. They are the Ampere-Hour integral method with combined model,

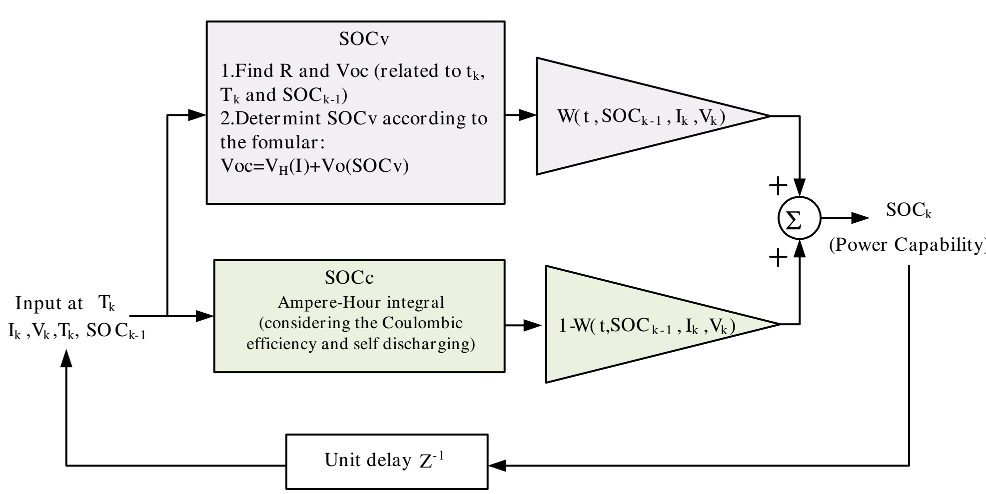


Fig. 8. weighted fusion algorithm (adapted from [65]).

Rint model (simple model), the Rint model with the zero-state hysteresis model, the Rint model with the one-state hysteresis model and the enhanced self-correcting model. Wang et al. [84] study the Kalman algorithm of Ampere-Hour integral method and second-order RC model method. Xia et al. [85] study the Kalman filtering method of Ampere-Hour integral and first-order RC model, pointing out that the meaning of EKF as a state observer lies in: when the Ampere-Hour integral method is used to estimate SOC, the voltage of the capacitor is estimated and then the estimation values of the cell terminal voltage are obtained to act as a basis for correcting SOC; meanwhile noises and errors are taken into consideration, filtering gains of each step is determined, the weight of the electromotive force in the calculation of SOC is obtained and eventually the optimal estimation of SOC is obtained. In this way, the Ampere-Hour integral method and the model-based SOC estimation method are combined organically and the latter overcomes the shortcoming of cumulative errors of the former, thus achieving SOC closed-loop estimation. Meanwhile, since the influence of noises is taken into consideration during the calculation, the algorithm has a strong inhibiting effect on noises. Shi et al. [86] study the Kalman filtering method of the Ampere-Hour integral method and the Nernst model. Fan et al. [87] study the Kalman filtering method of the Ampere-Hour integral and the first-order RC model. Mao et al. [88], based on the Ampere-Hour integral method and the first-order RC model method, realize SOC estimation under nonlinear conditions by adopting the unscented Kalman filtering (UKF) algorithm. Charkhgard et al. [89] use the Kalman filtering to integrate the Ampere-Hour integral method and neural network model method. The core content of the Kalman filtering method used for SOC estimation is to establish a reasonable battery equivalent model and build a group of state equations. Accordingly, this method is highly dependent on the battery model and an accurate battery model is needed to be established to obtain accurate SOC. In order to save computations, the model should not be too complex. Besides, another disadvantage of the Kalman method is that the Kalman gains are not easy to determine. If the selection of the gains is undesirable, the state will disperse [90].

In order to overcome the shortcomings of the Kalman filter method, Kim [90] puts forward a slip mode observer technology, which possesses strong robustness against the uncertainty of the model parameters and disturbance.

The different SOC estimation algorithms are compared in the Table 3. The SOC estimation error of each method is summarized in Table 4. For pure EV, Ampere-Hour integral method with correction by open circuit voltage and SOC calibration after full charging is simple and suitable. For HEV, On the basis of the analysis and comparison of the 12 battery models by the literature [67] and the above analysis, we think that the system formed by the first-order RC model with one-state hysteresis and the Ampere-Hour integral, combined with the algorithm of the adaptive control theory, is supposed to be most suitable, and this method is also suitable for pure EV.

3.2.2. *SOH estimation algorithms*

There is still no consensus in the industry on what SOH is and how SOH should be determined. State of health (SOH) is a figure of merit of the present condition of a battery cell (or a battery module, or a battery system), compared to its ideal conditions [91]. The unit of SOH is percent, and 100% means it is a fresh battery. The SOH could be derived by capacity and the internal resistance, and it

Table 3
Comparison of the SOC estimation methods.

Method	Advantage	Disadvantage	Input
Discharge test method	Accurate, easy	Long time needed, offline, energy loss.	Remaining charge, capacity.
Ampere-hour integral method	Easy to implement, accurate if the initial SOC value, the current measurement and the efficiency is precise.	Depends on the initial SOC value. Needs accurate value of the self-discharge rate and the coulomb efficiency. Needs high accurate measurement of the current. Not suitable for batteries under very dynamic conditions.	Current, capacity, coulomb efficiency, self-discharge rate, initial SOC value.
Open circuit voltage method	Easy to implement. Accurate.	Needs some rest time. For some kinds of battery like LFP, it is only suitable when the SOC is very high or very low.	Rest time, voltage.
Battery model-based SOC estimation method	Needs no rest time. Insensitive of the initial SOC value.	For some kinds of battery like LFP, it is only suitable when the SOC is very high or very low. Sensitive to the measure noise.	Current, voltage. Battery model.
Neural network model	Suitable for all kinds of batteries.	Needs large amount of training data.	Current, voltage, cumulative charge, initial SOC, etc.
Fuzzy logic	Fuzzy thinking of human beings.	Not accurate.	Current, voltage, etc.
Resistance based methods		AC impedance: hard and cost. DC resistance: not so accurate.	Resistance.
Weighted fusion algorithm	Consider both the Ampere-Hour integral method and the battery model-based SOC estimation method.	Lot computation. Instability if the weight factor is not suitable.	Current, voltage, capacity, coulomb efficiency, self-discharge rate, initial SOC value. Battery model.
Kalman Filter	Accurate, dynamic. Insensitive of the noise and the initial SOC value error.	Lot of computation. Complicated. Instability if the gain is undesirable.	Current, voltage, capacity, coulomb efficiency, self-discharge rate, initial SOC value. Battery model.
Sliding mode observer	Accurate, robustness, dynamic. Insensitive of the noise, model error and the initial SOC value error.	Nonlinear. Not easy to implement.	Current, voltage, capacity, coulomb efficiency, self-discharge rate, initial SOC value. Battery model.

Table 4
SOC estimation error of the different SOC estimation methods.

Author	Year	SOC estimation method	SOC estimation error
V. Pop	2006	OCV method	Max 1.2%
H.W. He	2012	Battery model-based SOC estimation method	Max 4.327% Mean 1.423%
E.H. Liao	2011	Neural network model	Max <4%
K.T. Chau	2004	Neuro-fuzzy inference system	Mean <1%
J. Wang	2007	Fuzzy logic	Max <10%
M. Verbrugge	2004	Weighted fusion algorithm	Max <10%
C.Y. Xia	2007	EKF	0.7%
P. Shi	2006	EKF	Max <4%
Q.H. Mao	2010	UKF	Max <3.85%
M. Charkhgard	2010	EKF (Model is from Neural Networks)	Mean 3%
Il-Song Kim	2006	Sliding mode observer	Max <3%

could also be derived by other battery parameters like AC impendence, self-discharge rate, and power density. Take the capacity as an example, SOH could be defined as the ratio of the current capacity and the rated capacity given by the manufacture [24]. Generally, if the battery capacity is 80% less than the initial value, which means the SOH is less than 80%, then the BMS would warn the user to change the batteries.

The SOH decrement of a battery cell is mostly caused by the battery aging and degradation, namely, durability problems. That means with the using or storing of the battery cells, the battery capacity would decrease and the internal resistance would increase. Thus the SOH of the battery cells worsen.

Durability is a research focus of current industrial field and the major parameters characterizing the durability of batteries are capacity and internal resistance. Generally, the performance degradation of energy batteries (like batteries employed in EV) is characterized by the capacity fade and the performance degradation of power batteries (like batteries employed in HEV) by the increment of internal resistance. For the battery in the PHEV which requires both enough energy and sufficient power, both the capacity and internal resistance should be considered.

Like the SOC, the SOH of a battery module (or a battery system) is complicated. The capacity of a battery module decreases may be caused by the capacity decrease of every cell in the battery module, but the battery variations could be a possible reason. In this case, the battery SOH could be fixed by balancing. The internal resistance of a battery module increases may be caused by the resistance increase of every cell in the battery module, but screw looseness would also be a reason and after tightening the screws, the problem of the SOH could be treated. Those SOH decrement is reversible and could be considered as sub-health.

There are also some irreversible SOH decrements which are not caused by the aging, like battery damage caused by vehicle collision, battery short circuit caused by water, etc.

So, the aging of batteries is just normal performance degradation and cannot fully characterize the SOH. Most current SOH definitions are only limited to the category of the aging of batteries rather than actually involving the battery SOH (such as health, sub-health). Consequently, it is more appropriate to call current algorithms as state of life (SOL). However, it is important to find the battery aging mechanism and determine the battery capacity and resistance during the battery operating.

The main aging mechanism of the C/LFP batteries is [92]: the metal ions of the positive electrode have side reactions with the electrolyte and then dissolve in the electrolyte and have reduction reaction with the negative electrode during the cycles or storage and form SEI film, reducing the quantity of active lithium-ions. In terms of operating conditions, the major factors that influence the life and safety of batteries are: high temperature [93–96] (side reaction intensified); extremely low temperature (it is easy for material lattice to be damaged and for metal ions to be reduced); high potential or overcharge [93–97] (it is easy for electrolyte to decompose and have side reaction with the positive electrode and for lithium-ions to be reduced at the negative electrode); over-discharge [96] (it is easy for the copper foil of the negative electrode to corrode and for the active material lattice of the positive electrode to collapse); high charge/discharge rate [97] (the rise of temperature leads to the intensification of side reactions and the active material crystal lattice is easy to fatigue and collapse).

Currently SOH estimation methods mainly include: (1) durability model-based open-loop SOH estimation method; (2) battery model-based parameters identification closed-loop SOH estimation method.

3.2.2.1. Durability model-based open-loop SOH estimation method. Durability model-based open-loop SOH estimation method predicts directly the capacity fade and the internal resistance changes based on the battery durability model which includes durability mechanism model and durability external characteristic model [98–100]. The main difference of the two models is that the former places emphasis on the research of the internal side reaction mechanism of batteries and takes SEI film resistance, ion concentration and other microscopic quantities as its observation objects while the latter starts from experimental laws and focuses on the capacity fade and the internal resistance increment shown during the cycles and storage. Table 5 compares the two models.

Literature [100–103], according to the aging mechanism of the positive and negative electrodes and on the basis of the cyclic lithium-ion loss mechanism and the battery internal material corrosion mechanism, establishes a SEI film resistance increase model and a terminal voltage model after the performance degradation. Because the detailed aging mechanism of lithium-ion batteries is complex, the model parameters are hard to define accurately and also the computations are relatively large [100], usually the models are impractical to be used in the BMS in vehicle.

Quite a few literatures have touched upon the models based on external characteristics of batteries, among which the most common one is an Arrhenius-based model. Usually the batteries are cycled or

Table 5
Comparison of two durability models.

	Mechanism model	External characteristic model
Research method	Mechanism of lithium ion loss (metal deposition or lattice deformation), side reactions and SEI film thickening	Such external characteristics as capacity fade and internal resistance increment
Observation object	Concentration change of lithium ions in electrolyte, change of SEI membrane resistance and active substance particle size by scanning electron microscope	Capacity and internal resistance
Advantage	Clear principles, able to get a comprehensive understanding of the batteries aging	Simple and easy to predict capacity fade and internal resistance increment
Disadvantage	Complex, accurate design parameters and mass transfer coefficient input are needed, often influencing the precision	Based on a large number of experiments

stored at specific conditions, i.e. constant charge/discharge rate or selected temperature and the capacity loss or internal resistance increment with the cycle numbers or with time. To be simplified, usually only one or two factors would be considered to find the influence of these factor on the battery durability. Since under high ambient temperature, the battery degradation would be accelerated and the temperature is considered to be one of the most important factor which influent the battery life. Thus usually the durability experiment would be taken under different temperature and could not only accelerate the experiment, but also find the relation between battery aging and the ambient temperature.

Some examples are shown as follows:

i. The manual of Toshiba gives a storage life model for lithium cobalt oxides batteries [104], namely:

$$Q_{\text{loss}} = 1.544 \times 10^7 \exp\left(\frac{-40498}{8.3143T}\right)t \tag{7}$$

where Q_{loss} represents capacity loss percentage and its unit is %; T represents absolute temperature and its unit is K; t represents time and its unit is month.

ii. Bloom et al. [105] conduct experiments and analysis on the capacity fading rates of batteries at different ambient temperatures, and the battery capacity fade model which taking temperature as accelerated stress is verified, then the relationship between the battery performance degradation and ambient temperatures and cycle time are discussed and expressed as:

$$C_{\text{loss}} = Ae^{-\frac{E_a}{RT}} \cdot t^z \tag{8}$$

where C_{loss} represents area specific impedance (ASI) or power and its unit is Ω or W; A is constant; E_a represents active energy and its unit is J; R is gas constant and its unit is J/(mol K); t represents time and its unit is h; z is exponent of time and can take 1/2 under simple conditions. A, E_a/R, z can be obtained by fitting the experimental data.

iii. Based on the work of Bloom and others, Wang et al. [106] propose a double-factor model which takes Ah-throughput as variable, obtain a battery life model which takes temperature and discharge rate as accelerated stress by multiplying the time with the discharge rate and achieve a prediction error within 20% under double stress acceleration,

$$Q_{\text{loss}} = Ae^{-\frac{E_a}{RT}} \cdot (A_h)^z \tag{9}$$

where A_h represents ampere-hour and its unit is Ah; other parameters are the same with those in Eq. (8).

iv. Matsushima [107] studies the performance degradation of large-scale lithium-ion batteries, also find out that capacity loss have a square root relationship with the time, namely:

$$Q_{\text{loss}} = K_f \times t^{\frac{1}{2}} \tag{10}$$

and find out that the coefficient K_f of capacity loss within 30% is different from that of capacity loss above 30%. The former is greater, which indicates that the first 30% capacity fades rapidly in speed. And K_f complies with the Arrhenius law.

v. Extended models based on the Arrhenius model. For instance, in accordance with the experiments on the cycle life of lithium cobalt oxides batteries, Li et al. [108] put forward the following extended Arrhenius model:

$$Q_{\text{loss}} = \left(ae^{\alpha/T} + bI^{\beta} + c\right)n_c^{\left(le^{\lambda/T} + mI^{\eta} + f\right)} \tag{11}$$

where n_c represents charge/discharge cycles; I is discharge current and its unit is A. a, b, c, l, m, f, α, β, λ, η are all constants and can be determined by fitting through experiments,

vi. Li et al. [109] consider comprehensively many factors that influence battery life, such as ambient temperature, discharge rate, discharge cut-off voltage, charge rate and charge cut-off voltage, put forward a life modeling method based on coupling strength judgment and multi-factor input (in this model the influence of temperature also makes reference to Arrhenius modeling method and the influence of electric physical factors makes reference to inverse power law), and on the basis of factor sensitivity of the model, analyze the weights of influence of all factors on the battery life. The prediction error of the durability model for the battery life is within 15%.

vii. Other external characteristic modeling methods also include neural network model. For example, Jungst et al. [110] establish a neural network model when studying the storage life of batteries that take $LiNi_{0.8}Co_{0.15}Al_{0.05}O_2$ as the positive electrode material.

The above traditional models are mostly experience models obtained from experiments under controlled conditions and cannot characterize accurately the performance degradation of power batteries in vehicles for they take no account of the actual varied working conditions of vehicle operation. Especially, the battery aging process under different duty cycles are not discussed in these models. The further study of the battery aging and degradation is still needed. Recently, there are some recent works consider these problems and develop some new ideas.

Dubarry et al. [111,112] discuss the path dependence of the battery degradations and the aging process. A model which synthesize several cell aging scenarios based on degradation modes, including loss of active material, loss of lithium inventory, kinetic degradation or increase of polarization resistance, formation of parasitic phases, Li plating, is built.

Based on the research results of mechanical fatigue, Safari et al. [100,113] adopt the Palmgren–Miner (PM) method commonly used in mechanical fatigue research to predict the capacity fade of battery under simple and complex working conditions and make comparisons with capacity loss accumulation over time (LAT) method, finding that PM method is superior to LAT method.

3.2.2.2. Battery model-based parameters identification closed-loop SOH estimation method. The battery model-based parameters identification observation closed-loop method, based on existing battery models such as models introduced in Section 3.2.1, adopts optimal state estimation technologies such as the least square method, Kalman filtering and other algorithms, identifies such battery model parameters as capacity and internal resistance according to the operating data and then obtain SOH of batteries. And this method could also deal with the SOH changes not caused by aging.

Plett [114] takes internal resistance and capacity as the system state parameters and adopts the EKF to obtain SOH. The state estimation function of internal resistance is shown as follows (Rint model is adopted):

$$\begin{aligned} R_{k+1} &= R_k + r_k \\ y_k &= OCV(Z_k) - R_k i_k + e_k \end{aligned} \tag{12}$$

where R_k represents the internal resistance of batteries, and it is basically considered stay constant and its change is characterized by a speculative noise r_k; y_k represents the estimated operating voltage of batteries; i_k represents the operating current of batteries; Z_k represents SOC of batteries, which can be estimated by another EKF (thus dual EKF are formed) or obtained through other methods; e_k represents the error of battery model.

Likewise, the state estimation function of capacity C is

$$\begin{aligned} C_{k+1} &= C_k + r_k \\ d_k &= Z_k - Z_{k-1} + \frac{\eta_i i_{k-1} \Delta t}{C_{k-1}} + e_k \end{aligned} \tag{13}$$

Function (13) is a modification of ampere-hour integral formula and structurally the estimation value of d_k equals 0. Likewise, Z_k can be SOC estimated by another EKF (thus dual EKF are formed) or obtained through other methods.

Gould et al. [115,116] also identify the capacity in battery models on the basis of Kalman filtering method and linear fitting method and then obtain the capacity fade along with operation times. Besides, regarding the internal resistance in the battery equivalent circuit model as low frequency impedance, the slip mode control technology is adopted to identify the resistance [117].

Remmlinger et al. [118] introduce a battery internal resistance on-line identification method for hybrid motor vehicles. First in order to be able to realize on-line application, they modify the second-order RC model and increase the computation speed. Then on the basis of special load signal (transient voltage and current when the engine starts), they employ the linear least square method to obtain the internal resistance value of the battery model.

Verbrugge et al. [119,120] believe that the Kalman filtering algorithm is the most representative method for recursive parameter identification if we have a good understanding of the system's state parameters, measurement parameters and the evolution of noises. But if there is a lack of comprehensive understanding of the state parameters, measurement parameters as well as noises, the recursive least square method with time weighted exponential forgetting factor would be a practical method. They use this method to identify several parameters of lead acid batteries, nickel–hydrogen batteries and lithium-ion batteries (including open circuit voltage, internal resistance and other parameters needed to be identified). They also study the influences of the fixed forgetting factor and the optimized variable forgetting factor on the identification effect.

Wang et al. [121] find that the battery model-based recursive algorithm which calculates the voltage through superposition integral adopted by Verbrugge becomes unsteady when the sampling frequency is high. Therefore, they improve the algorithm of the battery model and also adopt the weighted recursive least square method with exponential forgetting factor to identify the battery parameters (open circuit voltage, internal resistance and so on).

Chiang et al. [122,123] build a parameter estimation algorithm based on the battery equivalent circuit model by using the adaptive control method commonly used in linear or nonlinear control system. For the convenience of using the adaptive control technology, the equivalent circuit model of lithium-ion batteries is described by state function. The algorithm framework is shown in Fig. 9. The internal resistance and OCV of batteries can be monitored and estimated on-line, which are used to determine SOH and SOC, respectively. Filter 1 is used to filter the sampling data and guarantee the estimation precision. Filter 2 is a high frequency filter and is used to filter the high frequency disturbance of the identified internal resistance and OCV so as to estimate SOH and SOC more precisely.

3.2.3. SOF estimation algorithm

The SOC describes how the battery differs from a fully charged battery, and the SOH describes how the battery differs from a fresh battery. The state of function (SOF) is used to describe while the battery is employed, how the battery performance meets the real demands. The SOF is determined by the SOC, SOH, operating temperature and the charge/discharge history if needed.

For the battery used in the energy storage area, the SOF could be defined as the ratio of the remaining available energy in the battery and the maximum possible energy could be stored in the battery [124]. For battery employed in the EV and PHEV, the remaining electrical driving distance is important, thus while estimating SOF, this part should be considered.

For the battery used in the system which requires specific supplied power, the SOF should describe how the battery meets the power demands. Thus, the SOF could be defined as a yes/no logical variable [125], while the SOF equals 1 means the battery could meets the demands and SOF equals 0 means could not. However, it would be more preferred to define the SOF as this equation:

$$\mathrm{SOF} = \frac{P - P_{\mathrm{demands}}}{P_{\max} - P_{\mathrm{demands}}} \tag{14}$$

where P means the possible power the battery could supply, the P_{demands} means the demands of the power, and the $P_{\max}$ means the maximum possible supplied power of the battery (while the SOH and SOC equals to 0, and the operating temperature is at a specific temperature). The relations between SOF and SOC, SOH are shown

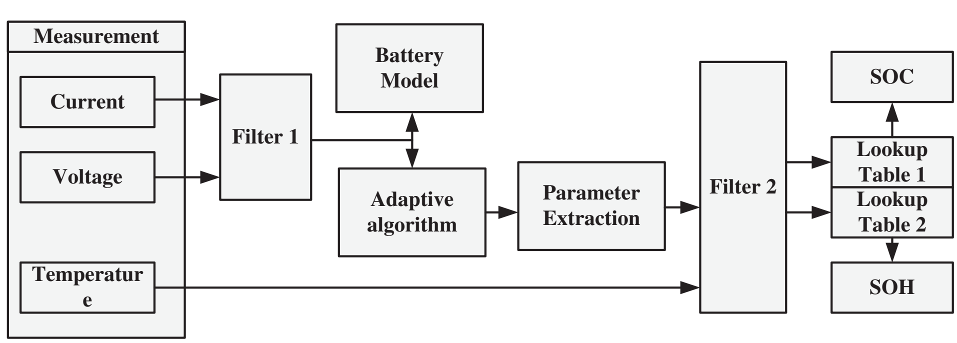


Fig. 9. SOC and SOH estimation algorithm framework using the adaptive control technology (adapted from [101])

in Fig. 10 (refer to [126]). SOF equals to 0 means the battery could barely meets the power demands. For battery employed in the EV, HEV and PHEV, the battery should meets the power demands of the motors (also includes the motors of the air conditioner), thus while estimating SOF, this part should be considered.

The SOF of a single cell is easy to get if the SOC and SOH of the cell are determined, but actually the SOF of the battery module is more meaningful and more complicated to be derived because of the battery uniformity problems. To find the SOF of the battery module, the model of battery module should be built from the cell model. M. Dubarry, et al. [127,128] consider the cell variations, discuss how to model them, and build battery module model from the cell model. According to the battery model and the SOC, SOH of each cell, the remaining energy and the capable power could be easily calculated. Thus the SOF of the battery module would be derived.

3.3. Battery uniformity and equalization

The battery uniformity refers to the phenomenon that though the battery packs is integrated by batteries of the same type and specification, there exist certain differences between each cells as voltage, SOC, capacity and capacity fade rate, internal resistance and its change rate, battery life, self-discharge rate and its change rate along with time [129]. During the process of production and packing, especially for power battery in vehicle, if the manufacturing environment of batteries is poor and the production line is not automatic but manual, it is inevitable to have relatively great differences between cells. Along with the battery operating time increase, the uniformity of power batteries in vehicle will worsen, which will eventually influence the life of the battery packs. The essential factor that influences uniformity is self-discharge rate which is influenced by such factors as temperature and SOC. The higher the temperature is, the greater the self-discharge rate will be [130–132] and the higher the voltage is (which means the greater the SOC is), the greater the self-discharge rate will be [133]. Meanwhile temperature is one of the greatest factors which influence the battery life. Accordingly, the non-uniformity of the temperature of battery packs exerts the greatest influence on the non-uniformity of battery performance and non-uniformity of other parameters such as internal resistance will eventually influence the uniformity of temperature.

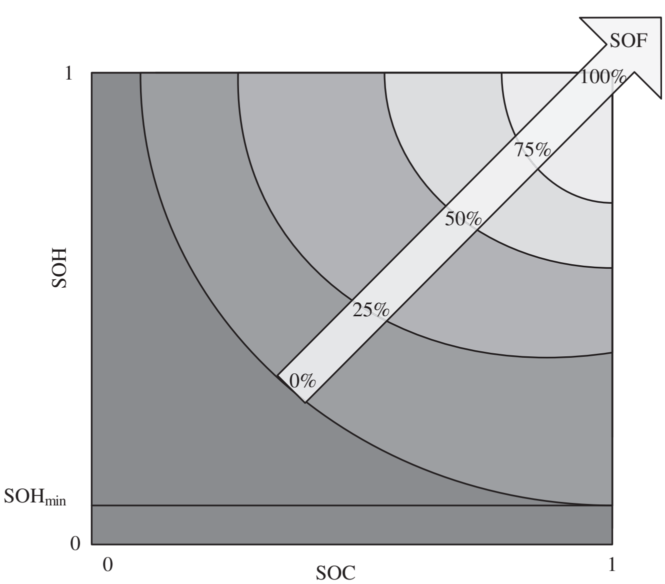


Fig. 10. Schematic figure of the relations between SOF and SOC, SOH.

The evaluation index of uniformity usually adopts a method of mathematical statistics and takes voltage, cell capacity, SOC and internal resistance as major parameters. Wang et al. [134] used the voltage mean value and variance method to study the change law of battery uniformity. Wei [135] adopts a probability statistics method to study the voltage uniformity of C/LFP batteries, believing that voltage distribution of batteries complies with the normal distribution. Chu et al. [136] used voltage overall dispersion and individual cell dispersion to characterize uniformity. The industrial standard QC/T743-2006 also evaluates the voltage uniformity of batteries in accordance with the standard deviation and standard deviation coefficient of cell voltage. The characterization of uniformity by the voltage parameter is suitable for battery systems (such as C/LMO, etc.) whose slope of SOC–voltage curve is steep and has high linearity while voltage uniformity is not suitable for evaluating such battery systems (such as C/LFP, etc.) whose slope of SOC–voltage curve is gentle and the slope change is great while SOC is very high or very low. The industrial standard of cell capacity uniformity is also characterized the standard deviation and standard deviation coefficient of cell capacity. It is suitable to adopt the cell capacity uniformity as the battery packing indicator while it is reasonable to adopt the remaining capacity of individual cells to characterize the uniformity of the operating battery after packing for the difference in the remaining capacity of individual cells is the major reason why the life of battery packs is shorter than that of individual cells. Since the capacity or remaining capacity cannot be directly measured, the above SOC and SOH estimation algorithms are needed to obtain these values.

The non-uniformity in remaining capacity mainly caused by the non-uniformity of self-discharge or Coulombic efficiency and equalization is needed to make compensation. The equalization method can be divided into chemical equalization method and physical equalization method [129]. The former realizes equalization by using some side reactions existing in batteries themselves during charge/discharge and it is only suitable for some types of batteries such as lead acid batteries and nickel–hydrogen batteries. For these types of batteries, the “overcharge” equalization method can be adopted to make the performance parameters of all batteries approach uniformity [137]. For lithium-ion batteries, it is needed to add oxidation–reduction additives to conduct voltage limiting protection. Otherwise, batteries would be seriously damaged and even lead to safety problems. The physical equalization method is to achieve equalization through external circuits and normally has two types: dissipation and non-dissipation. The dissipation method [34,138,139] is to dissipate the remaining capacity of individual cells that need to be equalized in battery packs through resistances or other means and achieve the goal of equalizing the remaining capacity differences between various cells within a battery pack. The non-dissipation method is to use a mobile shunt component or a voltage or current converter to transfer energy from one cell to another cell. These components can be analog or digital. The topological structures of the non-dissipation method include capacitor + switch array [140], scattered DC/DC converter module [138,141], coaxial multi-winding transformer [33,142], current redirector [143] and independent charging [144]. Since self-discharge exerts the greatest influence on uniformity, the function of equalization is mainly to compensate the non-uniformity caused by self-discharge. The self-discharge rate of lithium-ion batteries is usually very low, 3–5% per month. The time of equalization for BMS in vehicle can be relatively long; therefore, the current needed for equalization could be relatively low. Meanwhile the battery non-uniformity emergence is a very slow process (except the batteries have fault such as micro short circuit, etc.). Besides, using dissipative method, the structure is simple, does not consume much energy and can meet the demand of equalization.

All these help the dissipative equalization method to have wide applications at present. The non-dissipation method, although its efficiency is higher, has fewer applications due to such problems as its complex structure, poor reliability and difficulties in realization [145]. The equalization device of high current is usually used for the offline maintenance of batteries, which can save maintenance time.

The battery equalization algorithm can be divided into the equalization strategy based on voltage uniformity, the equalization strategy based on SOC uniformity and the equalization strategy based on remaining capacity uniformity.

Stuart et al. [145] designed a modularized BMS for large-sized batteries, which has both dissipative and charging equalization function, and adopts the battery equalization strategy based on voltage uniformity of batteries. Chen et al. [146] designed a bidirectional equalization method to realize charge/discharge equalization and adopts the equalization strategy based on voltage uniformity of batteries. However, the literature [147–150] equalizes the battery on the basis of SOC uniformity of individual cells. Jiang [151] adds the adaptive correction along with cycles to the remaining capacity estimation algorithm of medium-sized lithium-ion battery packs (5–10 Ah), solves the problem of low measuring precision of remaining capacity after numerous cycles and equalizes the battery on the basis of the characteristic that under the full discharge conditions SOCs of individual cells differ greatly from each other and are easy to be identified, which decreases the undesirable cases in which the voltage equalization is likely to make individual cells with high capacity but low voltage platform during discharge compensated with energy first and release energy to other batteries at last. Lin [152] believes that at present there is no mean that can calculate accurately the remaining capacity of batteries and thus it has no practical meaning to take SOC as the equalization objective since the measuring results of SOC has great errors. Lin holds that using the cell voltage uniformity as the equalization objective would be better to equalize the battery packs.

Although the battery equalization algorithm has many practical applications, the objective function is not clear and the equalization efficiency is not high. But in fact, behind SOC or voltage equalization methods, there is a common problem that needs to be solved: how to make use of the battery pack capacity. For a serial connected battery pack, it is clear that the battery pack capacity is always less or equal to the capacity of the cell with the minimum capacity. Thus the optimal equalization result is to make the capacity of the battery pack equal to that of the cell with the minimum capacity. Namely, while the battery packs are cycling, this cell can be both discharged fully and charged fully, and would not be overcharged and overdischarged. If this requirement is satisfied, the non-uniformity of the SOC, voltage and even the remaining charge of batteries are of no importance. Suppose that the total capacity of the individual cell with the minimum capacity in the battery pack is C_{t,min_cell} and its current remaining capacity is C_{r,min_cell}; for the ith cell, this cell could be any other cells in the battery pack, its total capacity is $C_{t,i}$ and its current remaining capacity is $C_{r,i}$. Then if all the cells in the battery pack have $0 \le C_{r,i} - C_{r,min\_cell} \le C_{t,i} - C_{t,min\_cell}$, the cell with minimum capacity can reach 100% DOD charge/discharge and the battery pack capacity would be equal to C_{r,min_cell}. At this time, there is no necessity for equalization, as shown in Fig. 11(a). In other cases as shown in Fig. 11(b), the cell with minimum capacity cannot be discharged fully otherwise the ith cell would be overdischarged, so it is a need to discharge the cell with the minimum capacity or charge the ith cell; for such cases as shown in Fig. 11(c), the cell with minimum capacity cannot be charged fully otherwise the ith cell would be overcharged, it is a need to discharge the ith cell or compensate the remaining capacity of the cell with minimum capacity. To adopt this ideal method, the total capacity of all the individual cells and their remaining capacity need to be identified. These problems could be solved by the adaptive control technology of SOC and SOH introduced in Sections 3.2.1 and 3.2.2, but it is still very difficult to put into practical applications.

3.4. Fault diagnosis

Fault diagnosis is one of the necessary technologies to ensure the battery safety. The battery management system standard [29] formulated by International Electrotechnical Commission (IEC) in 1995 requires that the battery management system for electric vehicles must possess certain battery fault diagnosis functions, including giving early alarms of unhealthy batteries and providing battery aging information. The Chinese standard "Technical Specification of Battery Management System for Electric Vehicles" [30] also has the requirement of battery fault diagnosis, stipulating the basic requirement items of fault diagnosis and extensible fault diagnosis items (in total 26 items) and classifying three levels of faults.

At present, the fault diagnosis technology has developed into a new interdiscipline. On the basis of the operating principle of diagnosis objects, it integrates computer network, database, control theory, artificial intelligence and other technologies. It has had mature applications in other fields. The basic methods of fault diagnosis are shown in Fig. 12 [153–157].

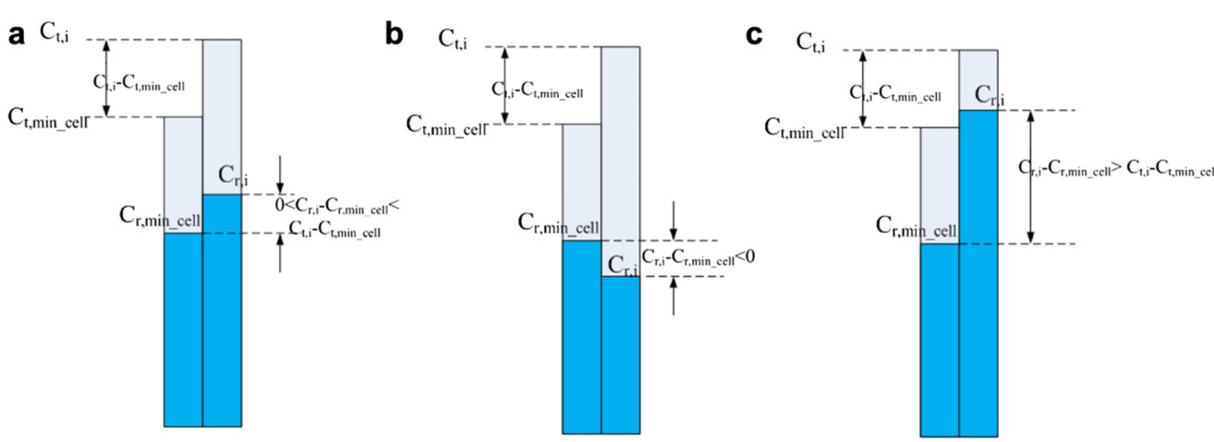


Fig. 11. Ideal battery equalization. (a) The battery pack needs no equalization. (b) The cell with the minimum capacity needs to be discharged or the ith cell needs to be charged. (c) The cell with the minimum capacity needs to be charged or the ith cell needs to be discharged.

The battery fault diagnosis technology is still developing and researches on it are mainly based on process parameter estimation, state estimation, experience based and other methods (similar to the above SOH researches). Bohlen et al. [158] realize on-line diagnosis of batteries through the model-based on-line identification of the battery internal resistance. D.P. Abraham et al. [159] prove from mechanism that the changes of battery electrodes are the reason for the battery internal resistance increment and the power degradation through gas chromatography, liquid chromatography, electron microscopy, X-ray spectroscopy and other technologies. On the basis of SOH of lead acid batteries, Sun [160–162], assuming the voltage curve under normal constant charge/discharge conditions is smooth, identifies the potential faults of battery packs by observing the changes of the charge/discharge curve. The characteristics of sample entropy and approximate entropy are used to eliminate the influence of current changes so as to identify the battery faults under varied current. Likewise, the analysis of battery uniformity also provides a method for fault analysis of battery packs.

Intelligent fault diagnosis system is based on the method of expert system and has found applications in fault diagnosis of other fields. It is usually composed of knowledge base, inference engine, interpreter, man–machine interface, integrated database and knowledge capture, as shown in Fig. 13 [153]. The knowledge base and the inference machine are the core technology and in some application condition the system could be working without the man–machine interface and the interpreter. The battery fault diagnosis can also make use of the intelligent fault diagnosis, but this is still in a research stage. Liu [153] researches a set of knowledge base construction and inference machine considering the battery fault diagnosis characteristics and designs an open knowledge base, which overcomes the shortcoming of poor adaptability of traditional fault diagnosis systems and effectively realizes the independence between the inference machine and the knowledge base. Liu [163] constructs an expert system of battery fault fuzzy diagnosis, which (1) analyzes the relation between the data changes of battery external characteristics and the battery faults and summarizes diagnosis rules for common battery faults in combination with the experience and knowledge of battery

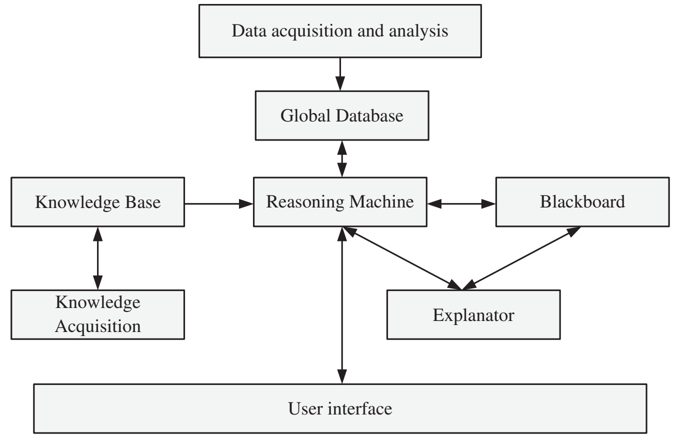


Fig. 13. Intelligent fault diagnosis system structure (adapted from [127]).

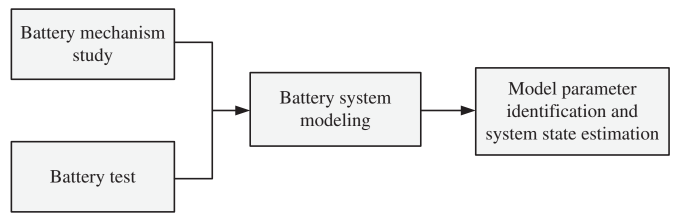


Fig. 14. BMS research process.

experts; (2) builds a fault diagnosis model for battery packs in combination with the theories of fuzzy mathematics and puts forward a solution method for battery symptom membership, determining the health level of batteries according to the fault membership. Through the expert diagnosis system, the early diagnosis of unhealthy batteries is realized. Wu [164], learning from the methods used in literature [163], also develops a battery fault expert diagnosis method based on fuzzy logic used for remote monitor and control system.

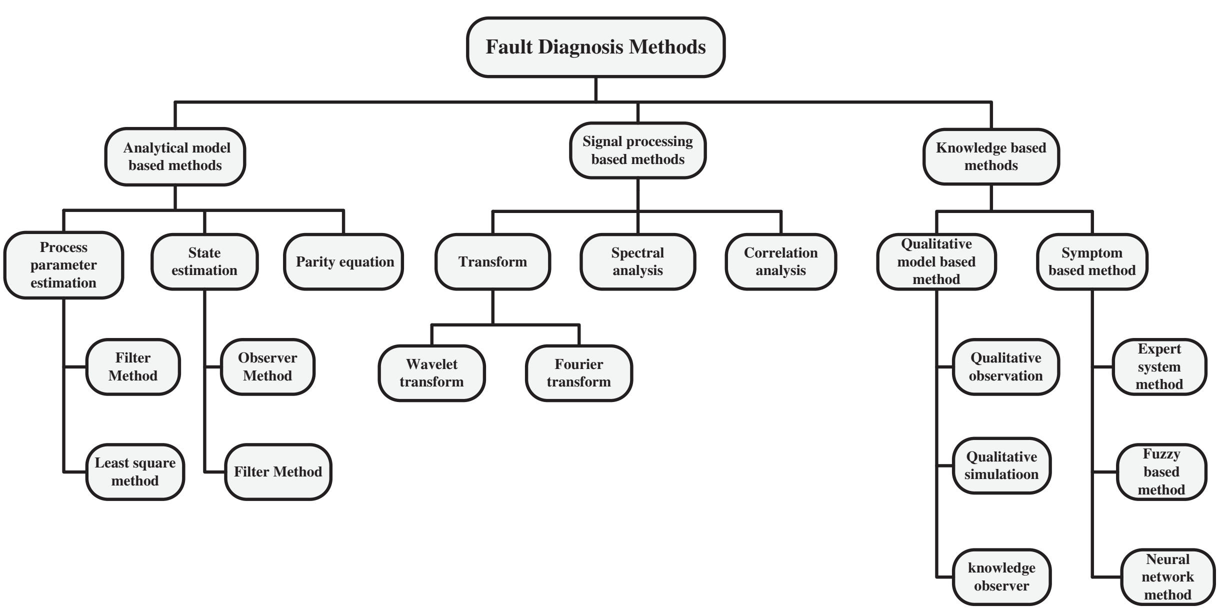


Fig. 12. Typical fault diagnosis methods.

4. Conclusion

To sum up, the basic method and procedures of BMS research is indicated in Fig. 14. First through researches on the mechanism of the research object (namely batteries), a deep understanding of the battery performance evolution process and mechanism could be derived. Meanwhile, the battery performance would be tested, thus the major and minor factors that influence the battery performance as well as the influence laws could be determined. Using the modeling method based on mechanism, semi-experience or experience to form practical battery system models for BMS (with adequate precision and less complex computations). During operation, in accordance with collectable data, the adaptive control technology is adopted to on-line or offline identify the parameters of the battery system, estimate the states of batteries (SOC, SOH, SOF and faults) and inform the vehicle controller through the network so as to ensure safety and reliable operation of vehicles. Therefore, the issues that require intensive studies in the BMS are (1) studies on the battery performance; (2) the building of battery models with practicability; and (3) the application of the adaptive control technology or the expert system theories in battery management.

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