Journal of Power Sources 405 (2018) 18–29

Contents lists available at ScienceDirect

Journal of Power Sources

journal homepage: www.elsevier.com/locate/jpowsour

Review article

Towards a smarter battery management system: A critical review on battery state of health monitoring methods

Rui Xiong*, Linlin Li, Jinpeng Tian

Department of Vehicle Engineering, School of Mechanical Engineering, Beijing Institute of Technology, Beijing, 100081, China

HIGHLIGHTS

- A detailed classification of battery SOH estimation methods was presented.
- The strengths and weaknesses of SOH methods were compared and analyzed.
- Deficiencies of the existing research and the improving directions were pointed out.
- SOH estimation with ultrasonic is expected to add one-dimensional data to batteries.
- A prospect of future SOH management for battery application has been presented.

ARTICLE INFO

Keywords:
Electric vehicles
Lithium-ion battery
State of health
Degradation
Capacity
Impedance

ABSTRACT

To ensure the driving safety and avoid potential failures for electric vehicles, evaluating the health state of the battery properly is of significant importance. This study aims to serve as a useful support for researchers and practitioners by systematically reviewing the available literature on state of health estimation methods. These methods can be divided into two types: experimental and model-based estimation methods. Experimental methods are conducted in a laboratory environment to analyze battery aging process and provide theoretical support for model-based methods. Based on a battery model, model-based estimation methods identify the parameters, which have certain relationships with battery aging level, to realize state of health estimation. On the basis of reading extensive literature, methods for determining the health state of the battery are explained in a deeper way, while their corresponding strengths and weaknesses of these methods are analyzed in this paper. At the end of the paper, conclusions for these methods and prospects for the development trend of health state estimation are made.

1. Introduction

In order to cope with the dual pressures of environmental pollution and energy shortage, electric driven vehicles, which have variety of energy sources, flexible working modes and the potential of energy-saving and environmental protection, have become the key direction for the development of the automobile industry. Lithium-ion batteries (LiBs) are one of the commonly used onboard energy sources of the electric vehicles (EVs) [1–3]. The capability to store energy and provide a certain power decreases over the battery lifetime because of aging. So the state of health (SOH) as an important metric to assess the battery aging state is critical for safe and pleasant driving experience. Once the health indicator reaches the predetermined limit, the battery should be removed from the energy storage system and EVs [4].

The most used SOH indicators are battery capacity and internal resistance, which reflect the energy capability and power capability respectively [5,6]. From the study of internal aging mechanisms of different battery types, the loss of lithium inventory, active material decomposition, structural changes are the common reasons for capacity loss [7–9]. And the increase of resistance is mainly contributed to solid electrolyte interface (SEI) layer growth. Battery test procedures manuals define that when the battery capacity decreases to 80% of the initial rated capacity under a specific test protocol, the battery is deemed not suitable for vehicle application and need to be replaced [10]. But in some cases, the increase of the internal resistance resulting in power decrease obviously will lead to battery failure in advance. So considering these two aspects together is important for EVs to run normally. Battery characteristics which change significantly during the

* Corresponding author. Department of Vehicle Engineering, School of Mechanical Engineering, Beijing Institute of Technology, No. 5 South Zhongguancun Street, Haidian District, Beijing, 100081, China.

E-mail address: rxiong@bit.edu.cn (R. Xiong).

https://doi.org/10.1016/j.jpowsour.2018.10.019
Received 4 June 2018; Received in revised form 18 September 2018; Accepted 8 October 2018

aging can also indicate the increasing possibility of battery failure, such as charging curves, OCV (open circuit voltage) curves and so on [11–13]. To reveal the aging rule of these health related indicators, a large number of experiments have been done in the laboratory. Taking the online and simple implementation requirements for EVs application into account, much work has concentrated on model-based methods using different kinds of estimation techniques.

As an indispensable technique of BMS (Battery Management System), SOH estimation methods have been extensively studied using various tools and approaches. Unfortunately, the estimation of health-related characteristics, and therefore, of the SOH, might be a very challenging task. Because there are many factors like temperature and charge-discharge rates affecting the battery aging process, studying the aging rule under these factors need long time cycling tests and characteristic tests. Although most methods were verified sufficiently in the abundant experimental data, the feasibility and reliability of these methods on real vehicles still require further discussion. The laboratory, equipped with advanced equipment and technologies, provides a stable environment to collect high precision experimental data [14]. Yet the EVs are not well equipped as laboratory, mainly subject to cost. In addition, there are great differences between the simulated working conditions in the laboratory and the actual road conditions, which bring difficulty for SOH application. There is thereby an urgent need but it is a significant challenge to improve these methods for industrial application. Hence, a conclusion and analysis of these academic achievements should be made, which would offer researchers convenience and propose the future research direction. Although all kinds of methods have been proposed, only few literature aimed at a comprehensive review for methods on estimating SOH [2,4,15]. Combining analysis of the literature and our practical experience, authors in this paper try to demonstrate these methods in a clear way, with some suggestions for improving the existing methods and future SOH development.

This paper is organized as follows: the classification for the existing battery SOH estimation methods is introduced in Section 2. Different SOH monitoring methods and their challenges have been systematically elaborated in Section 3 and 4. In Section 5, comparison and prospects for SOH estimation methods are made. Ultimately, Section 6 concludes this paper.

2. Classification

Different literature has presented different SOH classifications, and each has its own characteristics. In order to track these degradation behaviors for the online management of batteries in BMS, the battery SOH estimation methods in this paper are divided into two categories: the experimental methods and model-based estimation methods. There are two branches below each major category and each branch contains several common methods, which are shown in Fig. 1.

The characteristics and challenges of each approach are analyzed below.

3. Experimental methods

Experimental methods require a large number of experiments carried out in the laboratory to analyze the battery aging behavior. Owing to the need of corresponding experimental equipment and the great difference between actual driving conditions and laboratory environments, some experimental methods are difficult to achieve on-board. But they can be used to study the aging mechanisms, providing theoretical basis for model-based methods.

Experimental methods encompass direct measurement methods and indirect analysis methods. Direct measurement methods use capacity tests, impedance measurements and other tests to measure the battery health state indicators directly. Indirect analysis methods require data analysis and processing to find the SOH related parameters.

3.1. Direct measurement methods

The direct measurements can be used in lots of specific forms of implementation and calculations, like: capacity or energy level, AH counting, ohmic resistance, impedance, cycle number counting, destructive methods and so on.

3.1.1. Capacity or energy level

The energy capability, which determines the achievable mileage of EVs, is defined by the battery capacity. The battery capacity reflects how much energy can be stored into a fully charged battery, and thus is widely used as SOH indicator. If the present capacity of a battery can be measured accurately, the SOH can be determined directly. It is the easiest and most precise way. There are mature capacity testers in the market which can measure capacity accurately. Unfortunately, for a running EV, it is difficult to stop and measure the fully charged capacity. Therefore, the method would be only usable at fixed environments, such as the laboratory, to calibrate the capacity. In order to solve the problems that the capacity/energy cannot be measured in real-time, a number of online estimation, prediction or identification methods for battery capacity have been proposed with the development of the BMS, which will be further discussed in Section 4.

3.1.2. AH counting method

Through the high precision measurement technique, the charge transferred through the battery during full charge-discharge process is accurately counted, so thus the remaining capacity can be simply calculated. The computation equation of SOH is shown in Eq. (1):

$$SOH = \frac{Q_{\max}}{Q_{\mathrm{n}}} \times 100\% \tag{1}$$

where $Q_{\max}$ is the maximum available capacity of the present condition, Q_{n} is the nominal capacity of the battery.

To obtain accurate remaining capacity, long-term monitoring and memorizing of the battery current is an indispensable process, which costs lots of time and energy. And the accurate remaining capacity highly depends on the high-precision current sensor to reduce accumulated error. What's more, in the laboratory the battery is usually fully charged and discharged with small constant current at ambient temperature 20–25 °C to measure capacity. Obviously it is difficult to satisfy such conditions in EVs. Researchers always choose this method to verify the accuracy of capacity estimation results from other methods [4]. In Ref. [16], the authors used the Ah counting for state of charge (SOC) and SOH estimation. In the proposed method, however, SOH was re-evaluated in either fully charged or discharged states, which occur occasionally in EVs. As will be described in Section 4.1.1, AH counting method plays an important role in equivalent circuit model (ECM) for SOC and capacity estimation. By combining it with ECM, there is no need to fully charge or discharge the battery, which is more applicable to on-board usage.

3.1.3. Ohmic resistance or impedance measurement

The power ability of the battery is strongly correlated to its internal resistance. The internal resistance defines the voltage drop over the battery when the current is applied. To ensure that the battery is operated in the safety voltage range, the current rate applied on the battery is limited, therefore, the available power. As a commonly used parameter to indicate the health state of the battery, different techniques to measure resistance have been investigated extensively. For a LiB, the internal total resistance includes ohmic resistance and polarization resistance. While in normal working condition, the ohmic resistance contributes mostly to the voltage drop, which is basically linearly dependent on the current magnitude. Due to this reason, the ohmic resistance can be calculated following the Ohm's law. Fig. 2(a) plots a current and voltage profile in a discharge and charge pulse, where t_1 and t_2 denote two pulse intervals. Similar pulses can be

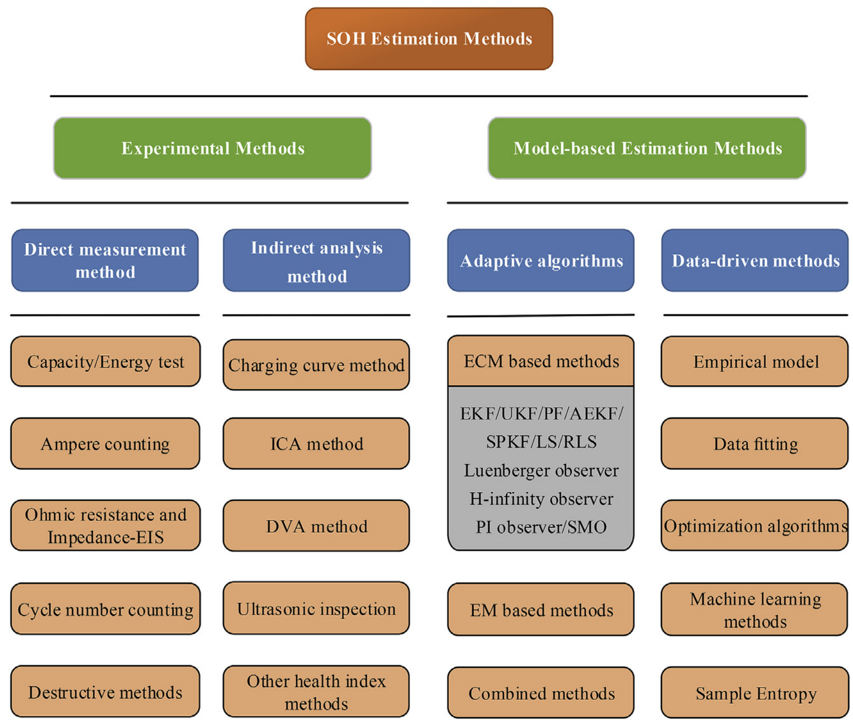

Fig. 1. Classification of battery SOH estimation methods.

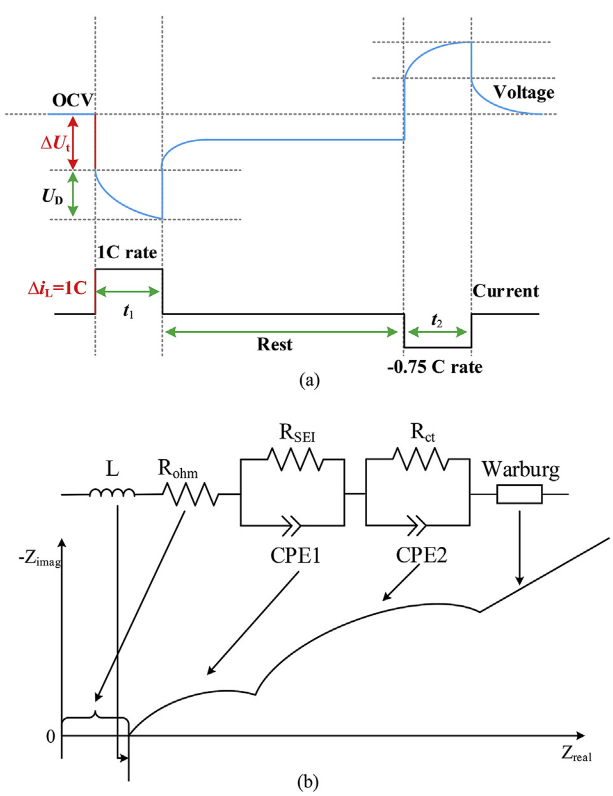

Fig. 2. (a) Current and voltage profile in a discharge and charge pulse, (b) corresponding relationship of EIS and electric elements.

obtained when the EV is in brake or accelerate condition, or in the specific pulse test. The ohmic resistance is obtained as [17]:

$$R_o = \frac{\Delta U_t}{\Delta i_L} \tag{2}$$

where ΔU_t denotes the pulse voltage, Δi_L denotes the applied current pulse.

Because a battery is a complex electrochemical device, the ohmic resistance is affected by the operation conditions and has relationship with many parameters like temperature and aging state. Based on this recognition, deep studies have been conducted to fund the relationships between the ohmic resistance and the influence factors. The authors in Ref. [5] used the current pulses methodology to study the dependence of the ohmic resistance on some parameters, which include temperature and SOC. It was concluded that temperature had a great influence on ohmic resistance, while the ohmic resistance had no significant dependency on SOC. Additionally, it should be noted that battery aging also has impact on the obtained rules in some degree. For example, in the experimental results of [5], the temperature dependence of the ohmic resistance remained in its exponential form over the battery lifetime and this relationship became increasingly obvious with ongoing battery aging.

Another method to measure ohmic resistance is Electrochemical Impedance Spectroscopy (EIS). The intersection of the spectra and real axis in a Nyquist plot is the ohmic resistance as can be seen from Fig. 2(b). EIS is a strong tool in laboratory to study the electrochemical process inside the battery and it can be used as a diagnostic tool. The general principle of this method is to measure the characteristic response which depends on the cell impedance when a sinusoidal signal is applied on the cell. Because EIS can measure battery impedance in a very wide frequency range, besides the ohmic resistance, parameters like double layer capacitance, SEI resistance and charge transfer resistance can be obtained [9]. The authors in Ref. [18] noticed that ohmic resistance increased linearly during the aging process from the experimental results. This regularity was used to determine the health state by defining the diagnostic map between ohmic resistance and the available capacity. Improved ECM is often used to reproduce the impedance spectra, generally using an inductor, a resistance, two parallel ZARC elements (a parallel connection of a resistor and a constant-phase-element) and a Warburg element, as shown in Fig. 2(b) [9]. Compared with the simple ECM, the improved ECM can capture more complex dynamics of the battery with the sacrifice of computational efficiency [19].

EIS is still a relatively under-utilized method because there are still challenges to use it practically. As is pointed out in Ref. [4], although the SOH information obtained by EIS analysis is valid, as the battery type changes, there will be greater fluctuations. So, it is necessary to combine all possible types of battery to establish calibration platform with the use of battery identification algorithm. However, the cost and complexity are not easy to conquer. Moreover, EIS measurement needs long test time and a stable test environment, not convenient for on-board application. Considering the auxiliary devices for EIS measurement and the online application of impedance parameters, other ways to get impedance parameters are studied. The authors in Refs. [20,21] identified some impedance parameters based on the charging and discharging curves, which is free from the constraint of devices. But the proposed method relied on charging and discharging curves at constant current. So easier and more universal method to obtain online EIS parameters still needs additional research.

3.1.4. Cycle number counting

The number of cycles of a battery can be observed as the basis of the life model. This is a simple and direct way because only the counter for numbering the charge and discharge cycles is necessary. It is commonly used by the laptop or small electronic products such as nano-satellite [22] and phones for their SOH indication of batteries. If the total life cycle number of a battery is given by the manufacturer and the current cycle number which the battery has experienced is counted or calculated, the battery SOH can be calculated. This method primarily determines the SOH by recording the number of complete discharges (100% depth of discharge). For the case of not fully charging or discharging operation, the conversion coefficients are usually used to superimpose and convert the charges and discharges of different depths into full charge and discharge. The conversion coefficients can be calculated by experimental test.

3.1.5. Destructive methods

They are classical and direct methods for investigating the SOH and clarifying the aging mechanisms of the cells from the angle of micro-mechanism. Raman spectroscopy [23], X-ray diffraction [24], scanning electron microscope [25] and so forth, are most used techniques. Through the devices, the changes of micro structure during aging process can be observed. In Ref. [26], the authors studied the reasons of battery aging at storage condition. They pointed out that the leading cause of aging at high SOC storage is structure change in the positive electrode, including decomposition of active materials and the change of stress. However, to analyze the aging mechanisms using these methods, the batteries have to be disassembled, which will permanently damage the batteries. That is why they are deemed as post-mortem methods. Therefore, these methods are only appropriate for laboratory research.

3.2. Indirect analysis methods based on the measurements

With the analysis of entire degradation data of batteries, indirect analysis methods to get SOH information can be performed. The indirect analysis method is a typical multi-step derivation method using the health indexes which is associated with the degradation of battery capacity or internal resistance. After obtaining the relationship of the health indicators and capacity or resistance, the battery SOH can be obtained.

3.2.1. Charging curve method

The charging curve can be used to characterize the battery SOH because it will change as the battery degradation process. As long as the amount of data is complete, the method can be used for calculating SOH accurately.

Constant current and followed by a constant voltage with current limit (CCCV) charging mode is widely employed for batteries. A. Eddahech developed a SOH estimation method using CV step as health indicator. In their research [27], they simulated the battery current behavior during CV step by a simple expression as follows:

$$I(t,\, C_{\mathrm{loss}}) = A(C_{\mathrm{loss}})e^{-B(C_{\mathrm{loss}})t} + C(C_{\mathrm{loss}}) \tag{3}$$

where C_{loss} was the capacity loss, A, B and C were parameters which had corresponding relationships with the capacity loss. Through the current curve at the CV step, the parameters of the equation could be determined, so thus the corresponding capacity loss was found. Constant current charging mode without CV period can also be used to calculate SOH. In Refs. [25,28], quantitative analysis of aging mechanism was done by reconstructing charge voltage curves. The reconstructed charge voltage model contained five parameters which could be identified by optimal algorithms. The evolution of these parameters reflected aging mechanisms quantitatively. In these proposed methods, however, the impact of temperature on the charging curve was not discussed. The estimation accuracy might decrease when the battery is charged at different temperatures rather than 25 °C. And these methods were dependent on the particular charge mode, not usable on fast charging.

3.2.2. ICA and DVA method

Because very little internal information of the battery can be directly obtained from voltage curves, Dubarry et al. [29,30] used electrochemical characterization and analysis techniques, incremental capacity analysis (ICA) to process voltage data and get more sensitive curves. IC curves can be calculated by integrating capacity corresponding to small voltage intervals (dQ/dV) through charging or discharging the battery at very small current rate. This process converts the voltage plateaus of two-phase transition into recognizable IC peaks. Another method to get more aging information by processing voltage curves is differential voltage (dV/dQ) analysis (DVA). The distance between two peaks of the DV curve represents the amount of electricity participating in the two-phase transition, so it is easier to analyze

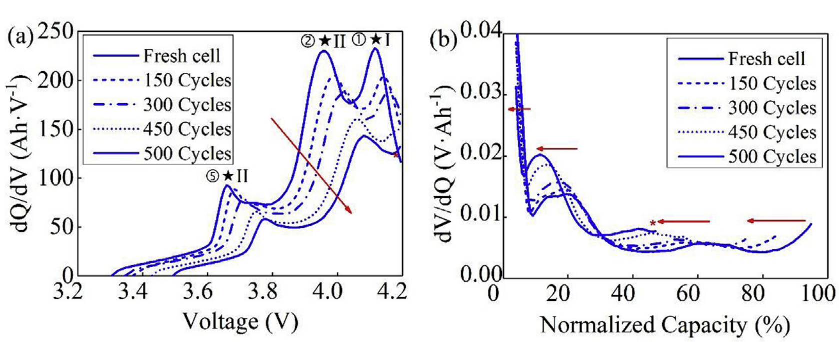

Fig. 3. Evolution of the (a) IC curves and (b) DV curves cycled at 40 °C and 50% DOD.

capacity fading in a quantitative way using the DV curves [28]. Besides getting the IC and DV curves by definition, polynomials can be fitted with the data and then differentiated for IC and DV curves [31].

Fig. 3 shows the evolution of the IC and DV curves cycled at 40 °C and 50% DOD and the change trends of the curves have been marked in the figure. It can be found that the IC and DV peaks at different aging states have unique shapes, amplitudes and positions, which is the key idea for indicating the SOH through the change of the peaks. The authors in Refs. [32–35] adopted the position value of the IC peaks as a signature of battery aging. The local interval between two peak points of the DV curve was used as SOH indicator in Ref. [36]. In the same work, transformation parameters of DV curve were also used to indicate the battery capacity loss due to the linear relationship between them. To get more stable results, ICA and DVA can be combined with machine learning methods. In Ref. [31], the authors used support vector regression to get IC curves and this method was verified using eight cells with less than 1% error.

For onboard application of ICA or DVA, some limitations of the method have to be overcome. Firstly, to evaluate the battery health state and ensure an accurate knowing of the aging mechanisms, IC and DV curves are always excited with a very low current rate, like C/25. However, it is very hard to accurately capture such a small current in practical application. Bigger currents like C/3 [28,37] and C/2 [33] have been used to analyze the IC behavior, with the compromise of accuracy. Secondly, traditional methods to obtain IC or DV curves usually require numerical derivation, which brings high computational effort to microcontrollers. Therefore methods with less computation like point counting method [28] and improved center least square method [36] were introduced. Thirdly, to get smoother curves by eliminating the noise of the curves, appropriate filtering and smoothing method is of importance. A smoothing method using Gaussian filter was proposed and the noise on the differential curves could be effectively filtered [33].

3.2.3. Ultrasonic inspection

Ultrasonic inspection is a convenient method to detect all kinds of minor defects inside the materials. It is an important non-destructive technique for quality checks and product maintenance. The application of ultrasonic inspection solves some difficulties of internal defect detection without disassembly, such as rail inspection [38] and composite materials inspection [39]. Recently, the scholars have begun to use ultrasonic technique to detect the inner changes during battery aging [13].

A typical ultrasonic inspection system is composed of pulser, receiver, transducer and a monitor. Receiver can receive the ultrasonic waves generated by the pulser. The reflection, refraction and wave pattern transformation will be generated at the vital interfaces of the battery, where degradation processes take place. With these characteristics, the reflected wave from the defect interfaces can be used for health diagnosis. As deciphered in Ref. [13], the change of vital interfaces during battery aging can be reflected by the waveform change compared with the waveform of new battery. Fig. 4 illustrates a possible combination of ultrasonic inspection and other techniques in a BMS. However this method for SOH estimation still needs further study and improvement. It is hard for end users to know the battery health state through the waveform on the monitor. Comparing the signal features with battery health state through machine learning methods may be a feasible method, which has been studied in other fields [38,39].

3.2.4. Other health index methods

There are also many other indirect methods depending on the experimental degradation data, such as voltage change [40], stack stress [12], internal pressure [41], etc. In Ref. [40], a linear dependence between the OCV obtained after full charging and 30-min rest and remaining capacity was found. This method was verified using three types of battery with different aging states at several temperature points. But the charging process before voltage measurement, such as initial SOC, would have an influence on the estimation accuracy. The authors in Ref. [12] measured the stack stress of the battery at different cycling numbers and noticed that there was a linear relationship between stack stress and SOH. The principle of this relationship was analyzed and attributed to SEI growth. Measuring internal pressure can reveal the gases generation caused by the chemical changes inside the battery. The authors in Ref. [41] found the correlation between internal pressure and capacity fade which would be a useful diagnostic method for damage and SOH prediction.

4. Model-based estimation methods

Although rich degradation information and accurate SOH estimation result can be obtained from experimental methods, online, real-time and reliable acquisition of battery health state is more desirable for BMS. Capacity, resistance and other parameters can be estimated based on a model with adaptive filtering or data-driven algorithms, and then be used to quantify the degradation of LiBs. The difference between these two categories lies on the computation procedure. Adaptive algorithms are commonly using the electrochemical model (EM) and ECM, and the closed-loop control and feedback are indispensable steps. While for the data-driven methods popular are the black box model and advanced classification, machine learning, intelligent optimization algorithms.

It should be noticed that the model-based estimation method is an extension of the indirect method, not simply depending on the real-time measured data, but to estimate or identify the characteristic parameters through filtering or intelligent algorithms.

4.1. Adaptive filtering methods

Adaptive filtering or observer method is popular for battery SOH estimation, and is also a progressing kind of method used in the BMS. Main implements have been elaborated in the following sections.

4.1.1. Equivalent circuit model based methods

The electrical model described by a circuit consisting of the basic elements, such as resistance, inductor, and capacitor, is called an ECM. Featured with the advantages of less computational burden and easy online application, ECM has been widely used for SOC or SOH estimation. Based on a battery model, the adaptive filtering and observer algorithms are good choices to identify the parameters. With the identified resistance, OCV and other characterization parameters, the battery SOH can be obtained by lookup table method. The lookup tables, obtained through long-term tests in laboratory, define data mappings between parameters and health state of the battery [42].

Kalman Filtering is an adaptive method which has received considerable attentions for battery parameter and state estimation. There are many derived and improved algorithms based on the KF algorithm, such as extended KF (EKF) [43], unscented KF (UKF) [44], Particle filter (PF) [45,46], adaptive EKF (AEKF) [47], sigma point KF (SPKF) [48], etc., to deal with the strong-nonlinear and high computational model. Fig. 5 presents a generic operation framework for identifying and estimating the battery parameters through the adaptive filtering or observer algorithms [49]. There are two steps to implement a KF algorithm. In the first step, a prediction state is required, where the filter estimates the current output variable. In the second step, the estimation is updated in order to obtain a more accurate result and give the estimation a higher certainty. Plett [6] used EKF algorithm to identify cell resistance and capacity by formulating simple models. Taking the cell resistance estimation as example, a simple model is formulated:

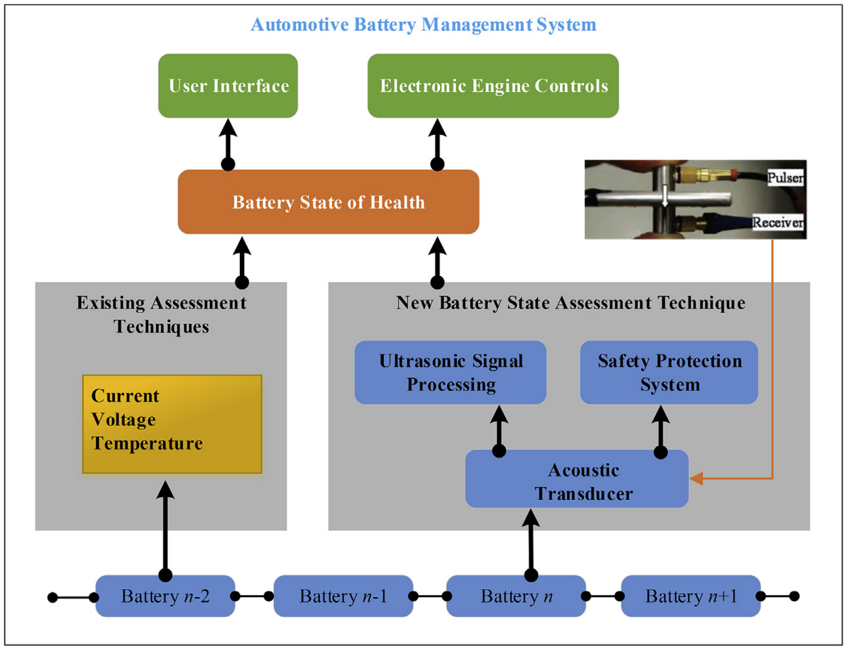

Fig. 4. Illustration of a BMS that uses the ultrasonic-transducer-based SOH assessment technique.

$$\begin{cases} R_{k+1} = R_k + r_k \\ y_k = \mathrm{OCV}(z_k) - i_k R_k + e_k \end{cases} \tag{4}$$

where R_k is the cell resistance, r_k and e_k are process noise and measurement noise, respectively, y_k denotes estimated terminal voltage, i_k is the load current, OCV is the open circuit voltage, z_k represents SOC which can be estimated from another estimator. Based on the definition of the state equation, the resistance can be identified using EKF algorithm in real-time. Rather than using a formulated model, in Ref. [50] parameters of the ECM can be arranged to appear linearly so that an adaptive filter method can be applied. The convergence of the proposed filter was proved by invoking the Lyapunov stability criteria.

The least squares (LS) [51,52] and its improved algorithm are also highly used in parameter identification because of their simple implementation and less computation. Using offline nonlinear least squares algorithm to identify model parameters is easy to achieve based on mathematics software but not feasible for real-time parameter acquisition. For online estimation of model parameters with recursive LS method, getting a discrete form of the dynamic equations is necessary. In Ref. [53], the model output equation is rewritten as the discretized form $y_k = \Phi_k \theta_k$ with bilinear transformation method, where y_k is the terminal voltage, Φ_k is the information matrix and θ_k is the unknown parameter matrix. Compared with other discretized forms in Refs. [54,55], OCV of the cell can be identified at the same time.

Considering that the parameters change constantly with the degradation and operating conditions, parameters of the model are

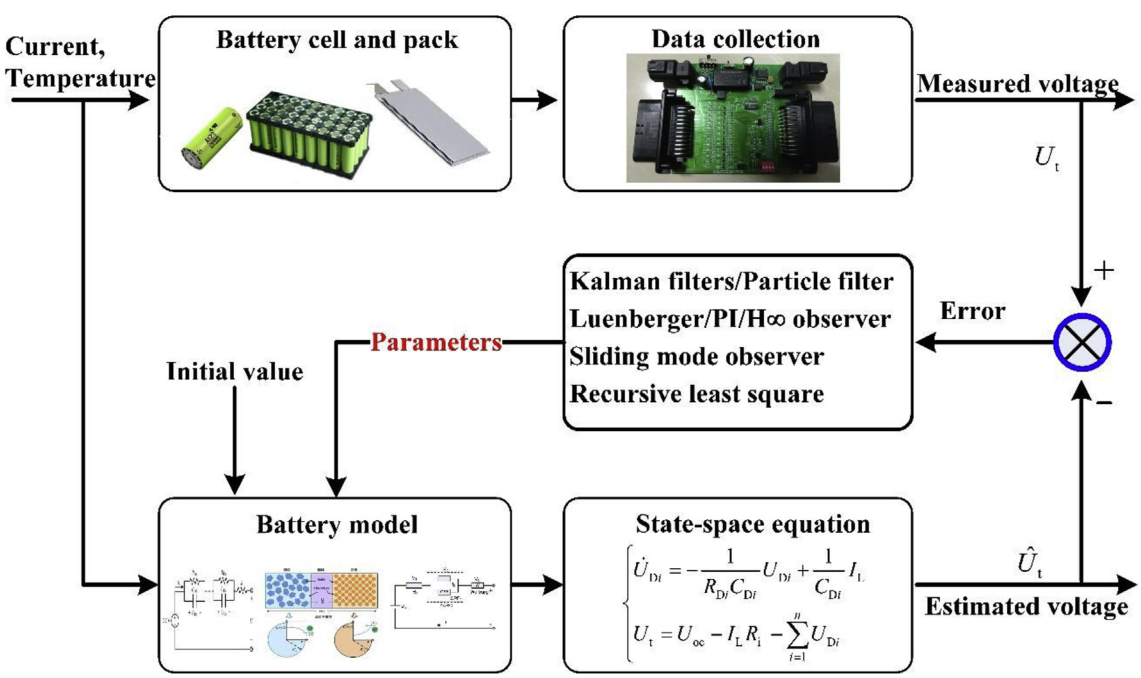

Fig. 5. Generic operation framework for identifying or estimating the battery parameters.

usually jointly estimated with SOC to improve the reliability and accuracy of SOC estimation. In Refs. [56,57], a joint estimation method was proposed using H-infinity and UKF, where the parameters were updated online by H-infinity. In Refs. [51,52,54,58], LS was combined with other filter algorithms to realize parameter and state estimation. Compared with other filter methods, LS is frequently used on microcontrollers, with the advantages of its matured application in many fields and easy improving. However, for very complicated battery model with strong nonlinearity, LS may bring inaccurate solutions and can even cause algorithms to become divergent [59]. Besides model parameters, capacity is also important health indicator which directly reflects the aging degree of the battery. The authors in Ref. [60] used two separate particle filters to estimate capacity and SOC. For PF, the amount of defined samples has an important effect on calculation speed and result accuracy, so reasonable amount of samples is crucial for practical application.

Because the SOH indicators are usually slow-paced time-varying parameters, it is not necessary to calculate SOH in every moment. If the system states and parameters are estimated at the same time scale, this will not only cause the system parameters change too frequently and reduce the stability of the estimation algorithms, but also increase the computation of the estimation algorithm and reduce the reaction rate of estimation algorithm. Based on the above considerations, researchers used different time scales to calculate parameters and state respectively. Multi-scale EKF [61,62], multi-scale PF [63], multi-scale nonlinear predictive filter [64] were developed and got good accuracy. The authors in Ref. [43] updated SOH offline with a trigger time of the SOH estimator when the error of SOC estimation was unacceptable.

Instead of identifying capacity directly, another feasible way to obtain battery capacity is developed based on AH counting equation as shown in Eq. (5) [65–67]:

$$Q = \int_{t_1}^{t_2} \frac{\eta i(\tau)}{3600} d\tau / (z(t_2) - z(t_1)) \tag{5}$$

where z (t_2)、z (t_1) represent SOC at time t_2、t_1 respectively, Q represents available capacity, η represents the coulomb efficiency. The computation procedure can be drawn by the Fig. 6. From the Eq. (4) we can see that the accurate capacity estimation is not only related to the accumulation of electricity in a certain time interval, but also depends on the accurate SOC estimation. In practical applications, the accumulation of electricity can use high-precision, high sampling frequency ammeter to improve accuracy, but the accurate SOC estimation is often difficult to obtain, because it has direct connection with the available capacity of the battery in the ECM.

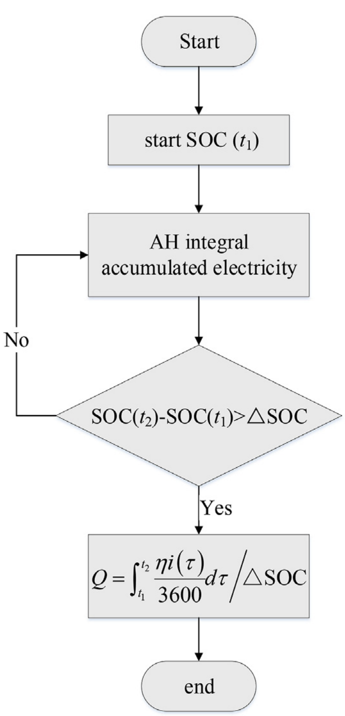

Fig. 6. Flowchart for the method of estimating the available capacity based on the SOC definition.

To better track the battery aging process, modified ECM was developed which can model the battery with more physical meanings. In Refs. [68,69], a half-cell model was developed by modeling the positive and negative electrodes separately. Although more complex model will increase the computational intensity, it can reflect more aging mechanisms compared with traditional ECM.

4.1.2. Electrochemical model based methods

EM was originally developed by Doyle, Fuller, and Newman [70,71], which comprised a serials of nonlinear and coupled partial differential equations. This kind of model was derived from the working principle of the battery, with the capability to describe the internal electrochemical dynamics of the cell. However, the solution difficulty and high computational pressure hinder its use for online application and state estimation. In recent years, many research institutes have contributed their effort on model simplification based on the traditional Pseudo-Two-Dimensional (P2D) model. A variety of simplification models such as single particle model (SPM) with less computation and acceptable accuracy have been developed and get widely used on state estimation, optimal charge and other aspects [72–76].

The principle of using adaptive filter method to estimate health state based on EM is the same as the ECM based method that is identifying health-related parameters. Adaptive output-injection observer [73], PI observer [77], EKF [78], multi-time-scale observer [79] and PF [78] were used to estimate battery resistance and capacity. Besides these two frequently used SOH indicators, electrochemical parameters which have a certain change trend as battery aging were estimated to indicate health state. The amount of cyclable Li-ions in the electrodes largely determines the battery capacity, often used for SOH estimation. Adaptive PDE observer [80] and EKF [81] were developed for SOH estimation using resistance and the amount of cyclable Li-ions as SOH indicators. However, the methods were verified by one set of data neglecting the influence of battery aging or operation conditions, as a result, the methods were not verified adequately. Solid state diffusion coefficient was used as SOH indicator in literature [82,83]. In Ref. [83], diffusion time, a variant of diffusion coefficient, was identified by offline linear least squares and on-line recursive parameter identification method. They identified the parameter at aged and fresh battery and found that the parameter varied monotonically with battery aging. So this parameter was excellent candidates for SOH estimation. EM can be combined with chemical/mechanical degradation physics models which reflect specific aging process. In Refs. [84,85], SPM was improved by considering the SEI layer formation, expressed by a relationship of SEI growth and cycling number. Integrating electrochemical model with different aging mechanism can reflect the specific aging reasons in a quantitative manner. But it is really hard to combine all the aging mechanism together.

4.1.3. Combined methods

Experimental methods can be combined with model-based methods. First, the aging mechanisms found from the experimental methods provide new ideas for model-based methods. Loss of both recyclable lithium ions and active material and the increase in resistance are the common causes in most graphite-based LiBs. One of the main contribution to loss of lithium inventory is Li-consuming SEI layer formation analyzed using ICA [29], so the increase of SEI resistance can be regarded as SOH indicator. The authors in Ref. [86] found the monotonic relationship between identified SEI resistance and remaining capacity through ECM. The method to estimate remaining capacity was effectively validated using aged and new battery with an error less than 3%. Furthermore, the parameters identified from the model-based method can be processed by experimental methods to get the battery health state. In Ref. [35], based on the OCV identified from the ECM, the authors used ICA to get the relationship of IC peaks and remaining capacity. The use of this kind of methods depends on the design requirements and the ability of the processor.

4.2. Data-driven methods

Due to the complex internal principles and uncertain working conditions, it is difficult to establish a battery model which can exhibit the battery dynamic characteristics accurately. The data-driven methods for SOH prediction do not need the knowledge of battery working principles and an explicit battery model, and they are only dependent on the collected aging data. However, to obtain rich and complete date, the experiments usually take several months and are costly, which are the main weaknesses of these methods.

4.2.1. Empirical and fitting methods

They use the available degradation data to predict the future behavior of LiBs without detailed knowledge of the electrochemical cell design and material characteristic. Polynomial, exponential, power law are usually used as fitting models. The computational simplicity of empirical or fitting models generally enables faster computation. The main aging factors considered in the papers are SOC, ΔSOC, end of charge and discharge voltage, DOD, temperature, aging time and the current.

Capacity loss models under different aging factors were constructed based on extensive experimental work [87–91]. In Ref. [87], Wang et al. developed a unified capacity loss model using the results from a large cycle-test matrix which includes three important parameters, temperature (−30–60 °C), DOD (90–10%), and discharge rate (C-rate, ranging from C/2 to 10C). The model is shown in Table 1, where R is the gas constant and T is the absolute temperature. Besides empirical capacity model, the scholars in Refs. [90,92–94] developed resistance models, which reflect the power capability of the battery. Empirical and fitting models highly depend on the experimental results, while it is difficult to guarantee absolute single variable. For example, in calendar aging process at different temperatures, the batteries are put in the thermotank at the aging temperature, hence the battery SOC might have a change because of self-discharge. In addition, the aging factors have a coupled influence on battery aging, it is hard to take all the factors into consideration to get a fitting result.

4.2.2. Optimization algorithms

They use the intelligent optimization algorithms to identify model parameters and then use one or more identified parameters to infer the SOH. Genetic algorithm (GA) is one of the mostly used optimization method which can estimate the parameters in a nonlinear system effectively. In Ref. [95], after obtaining the SOC-OCV-capacity mapping relationship, capacity and initial SOC were identified using GA based on ECM. In the process of model parameter identification, the changes of the model parameters are reflected by the errors of the terminal voltages between the estimation and experimental results. Different combinations of model parameters provide different terminal voltage errors. A set of parameters which can minimize the root mean value of the terminal voltage errors is the optimal set of model parameters. This method relies high on the OCV-SOC-capacity relationship. For batteries whose OCV-SOC curves don't change significantly as the battery aging or the SOC-OCV curves are flat, the identification result will have a large deviation. In Ref. [96], GA was applied to identify the parameters of the ECM. Then SOH was determined by the estimated diffusion capacitance, taking into account the temperature to improve robustness and estimation accuracy. GA got widely used in parameter identification of EM [81,97,98] due to the model's strong nonlinearity. The authors in Ref. [99] constructed the degradation trajectories of five electrochemical parameters over the battery whole life time by GA identification method. Then these five parameters were applied to represent the battery health state and the results were promising. Besides GA, other optimization algorithms like particle swarm optimization were also used for identifying health-related parameters [25,68].

Table 1
Generalized capacity loss model for all C-rates.

$$Q_{loss} = B \cdot \exp[(-31700 + 370.3 \times \text{C-Rate})/RT](A_h)^{0.55}$$
$$A_h = \text{cycle\_number} \times \text{DOD} \times 2$$

C-Rate	C/2	2C	6C	10C
B values	31630	21681	12934	15512

Because these algorithms need some time to find the optimal solution sets, the operation speed of the algorithm brings it challenge for practical application. In the light of rapid development in computers, online data can be stored and transported to a powerful computer to realize fast calculation. And Internet of Vehicles is an emerging field which has gotten much attention, the cloud computing platform of which has the great potential to solve this difficulty by the mass data storage and large-scale computing capabilities.

4.2.3. Machine learning methods

The goal of machine learning is to program computers by using example data or past experience to solve a given problem. With the extensive applications of artificial intelligence, machine learning methods, as the core technology, have been studied in various fields such as image recognition [100], financial sector [101], healthcare sector [102], etc. It is thus unsurprising that many research teams are applying it for battery state estimation. Support Vector Machines [103–105], Gaussian process regression [106], neural networks [107–109], Markov Chain [110,111], fuzzy logic [112,113], Monte Carlo [114,115], etc., are the main used machine learning methods for SOH estimation. These methods usually have a satisfactory result, but the access to training data is a real time consuming and costly process. Fortunately, the advent of big data platform could hopefully solve this problem. Considering that the big data technique has become a hot topic in vehicle field, the usage of machine learning will have enormous potential in health monitoring with the huge amounts of data. Once a big data platform is established, real-time monitored parameters like voltage, current and temperature will be stored and processed in the platform, which also decreases the requirements of the microcontroller. These mass data could be used as the training data of the machine learning algorithm which brings researchers lots of conveniences. How to select and filter data as the training data is important for these algorithms. Bad parameters selection will bring bigger error and the algorithms can even not converge.

4.2.4. Sample Entropy

The Approximate Entropy (ApEn) and Sample Entropy (SampEn) are important tools for quantifying the complexity of time series and studying the features of time series, widely used in many fields especially in the research of biomedical signals [116,117]. SampEn is an improved form of ApEn. SampEn not only has all the benefits of ApEn, but also eliminates self-matches and speeds up the computation. And SampEn is not sensitive to record length and shows improved consistency compared with ApEn [118]. Accordingly, when it is applied to battery data which have variation during battery aging, it could serve as an indicator for SOH estimation [119]. HPPC voltage sequence is highly sensitive to battery aging and often chosen to calculate SampEn as SOH indicator. In Ref. [120], the correspondence between capacity and SampEn from voltage sequence under HPPC profile was fitted by a polynomial equation. In Ref. [119], SampEn features were calculated from complete discharge voltage data at constant current, however

Table 2
Comparison of the SOH estimation methods.

Method	Advantages	Disadvantages	Improving directions
Direct measurement methods	● Most direct and simplest methods; ● Easy combination with model-based methods; ● Accurate in laboratory environment; ● EIS and destructive methods can be used to study aging mechanisms.	● Hard for online direct measurement; ● EIS and destructive methods require corresponding apparatuses; ● Destructive methods will damage the battery permanently and cannot be implemented in real-time.	● Online and easy EIS realization; ● Combined with suitable battery model; ● Develop offline maintenance and diagnosis strategies.
Indirect analysis methods	● Get aging information from the measured external characteristics; ● ICA/DVA and ultrasonic inspection can be used to study aging mechanisms in real time; ● Accurate in laboratory environment.	● Not suitable for all battery types; ● ICA/DVA/charging curve methods need particular working condition, such as constant current charge; ● Loss of accuracy due to the changing temperature; ● Difficult for online application.	● Methods to obtain online ICA and DVA curves with less computation complexity; ● Applied combining with machine learning methods; ● Considering the impact of temperature.
Adaptive filtering methods	● Accurate and good robustness; ● Easily applied for online battery energy storage with different chemistries.	● Algorithm development requires a lot of experimental validation and debugging; ● Need high performance controller; ● The precision highly depends on the model accuracy.	● Improve ECM with more physical meanings ● Improve EM with more aging mechanisms ● Develop a multi-model fusion method to improve applicability.
Data driven method	● Less pre-test required; ● Precise estimation of slowly changing parameters such as battery life and health.	● High requirements on the efficiency and portability of the algorithm; ● High dependence on the magnitude, sampling frequency, completeness, etc. of the transmitted data.	● Combining machine learning, big data mining methods with on-board adaptive filtering algorithms to improve the accuracy and robustness of onboard algorithms in real-time applications.

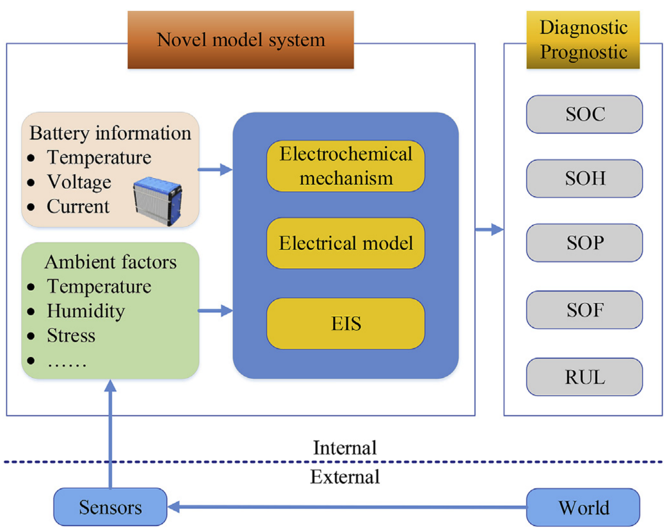

Fig. 7. A prospect for future novel model system.

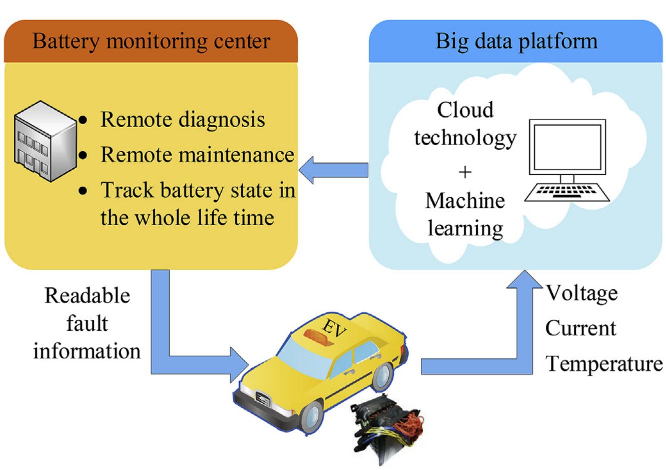

Fig. 8. A framework for combining BMS with big data platform.

such condition is rarely used in EVs. To get better and more accurate results, SampEn can be combined with machine learning method. SampEn is employed as the data input and the SOH (usually capacity) is the target vector of learning algorithm. SVM [119], relevance vector machine (RVM) [119] were combined with SampEn and showed very good performance. Besides voltage consequence, surface temperature of the battery can also be used as SampEn feature. In Ref. [121], by the combination of PF and SampEn calculated from the battery surface temperature, capacity fading was estimated with small errors.

5. Comparison and prospect

5.1. Comparison and analysis

Experimental methods store the whole degradation data and use them to analyze the change rules of main parameters during the battery degradation. It contains direct and indirect analysis. Direct measurement methods are the simplest and most direct methods, so offline maintenance and diagnosis strategies are suitable to be proposed based on these methods. The impedance tests and capacity tests can be performed regularly as parts of the reference performance test during the cycle aging test. Although they are difficult for real BMS application directly, they are indispensable methods in the laboratory to research various cell aging processes.

Indirect analysis methods need analysis and process of the measured external characteristics (usually including voltage, current and temperature). The analysis results are greatly influenced by the battery types, not applicable for all batteries. In other words, the linear relationship of selected SOH indicators and capacity may be failing when the batteries with different chemistries are studied. For practical application on EVs, the generality of the method should not be neglected, so validating these methods with different batteries is necessary. Now the measurable values of batteries are only current, voltage and temperature. To realize multi-dimensional monitoring of batteries, ultrasonic inspection is a good development direction.

Adaptive filtering methods evaluate the SOH by identifying parameters that are sensitive to the battery health state. They can reduce the dependency of performance on the battery data through the advanced filtering and state estimation methods and are easily applied for batteries with different chemistries. These methods are accurate but make a higher demand on microcontrollers. Some measures can be taken to improve the computational efficiency and release computational burden. For example, how to choose appropriate calculation step is a valuable research topic to reach a balance between estimation accuracy and calculation amount. Compared with EM, ECM needs less calculation but lacks physical meanings. Considering the different characteristics of these two models, combining them together to create totally new model or multi-model may be helpful for SOH estimation.

Data-driven methods are the popular methods, which require less pre-test work. The drawbacks of these methods are high requirements on the efficiency and portability of the algorithm and high dependence on the transmitted data. These methods have great potential for future health management system. Big data, cloud computing, cloud storage and other emerging technologies will solve the difficulty of data acquisition and improve the accuracy and robustness of onboard algorithms in real-time applications.

Most of the above methods were concentrating on the SOH estimation with single cells, while the batteries in EVs are generally connected in series and in parallel to construct a battery pack. Because of the uncertain operating conditions of EVs, it is difficult to ensure the uniformity of single cell. Thus health state monitoring for a battery pack with strong time-varying and non-uniform characteristics still need systematic theories and methods.

The comparison of these four principle approaches is shown in Table 2.

5.2. Prospect of future health management system

Because of its generality and online applicability, the future looks bright for the model-based methods both on laboratory and industrial scales. Along with the higher demand for accurately tracking the battery behavior, traditional single model cannot address the need of future BMS. Combining different models together will achieve complementary and get better results. As shown in Fig. 7, we propose an example of novel multi-model fusion system, which combines electrochemical mechanism, electrical model, frequency domain analysis and environment perception together. Multi-model will increase the model adaption to uncertain environment and different aging levels, so more accurate and reliable SOC/SOH/SOP/SOF and RUL (remaining useful lifetime) estimation can be achieved under complicated operation conditions. We believe multi-model will become the development trend to ensure the safety of EVs.

In recent years, how to make good use of massive data from EVs has been put on the agenda. As shown in Fig. 8, a simple framework of combining BMS with big data platform is proposed. In the daily driving process of EVs, voltage, current, temperature and other information are constantly transferred to a big data platform, which is constructed on the cloud technology. Based on the rich collected data, machine learning methods can be trained in practical environment and get better prediction results. Methods which need large computation and memory can be accomplished by the cloud computing technology. The data processing results will be transferred to a battery monitoring center. In this monitoring center, battery state and fault information in the whole life time can be recorded and stored. Real-time battery state and readable fault information will be transferred to EVs to realize remote diagnosis and maintenance.

In a word, the future development of battery SOH estimation maybe focus on the following three aspects: First, the introduction of new sensors to increase the capture of battery external and internal characteristics, such as ultrasound information, is a new perspective. Second, the battery model is updated and developed to be more suitable for parameter characterization of aging process and multi-model fusion method is a new research direction to improve the model adaptability. Finally, with the development of big data technique, the convergence of models and data, and the complementary coordination of off-line and online methods, will also enrich and improve the performance of SOH estimate.

6. Conclusions

This paper systematically summarized the state of art of the present battery SOH estimation, calculation and management methods. Although a large number of SOH estimation methods have been studied, each method has its deficiencies and possibilities for improvement. Further research and tests combined with engineering is necessary. Through this paper, the authors hope that for anyone with an interest in SOH estimation can benefit from this work. For engineers, appropriate method can be chosen to estimate the battery health state according to the actual demands. For researchers, we hope some inspirations can be obtained to further improve the SOH estimation method.

In future, advanced sensing, big data and data mining, and multi-agent decision-making techniques and methods will also be used to determining the SOH for batteries.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (Grant No. 51507012).

References

[1] M. Zackrisson, K. Fransson, J. Hildenbrand, G. Lampic, C. O'Dwyer, Life cycle assessment of lithium-air battery cells, J. Clean. Prod. 135 (2016) 299–311.
[2] L. Tao, J. Ma, Y. Cheng, A. Noktehdan, J. Chong, C. Lu, A review of stochastic battery models and health management, Renew. Sustain. Energy Rev. 80 (2017) 716–732.
[3] R. Xiong, J. Cao, Q. Yu, H. He, Critical review on the battery state of charge estimation methods for electric vehicles, IEEE Access 6 (2018) 1832–1843.
[4] M. Berecibar, I. Gandiaga, I. Villarreal, N. Omar, J. Van Mierlo, P. Van Den Bossche, Critical review of state of health estimation methods of Li-ion batteries for real applications, Renew. Sustain. Energy Rev. 56 (2016) 572–587.
[5] W. Waag, S. Käbitz, D.U. Sauer, Experimental investigation of the lithium-ion battery impedance characteristic at various conditions and aging states and its influence on the application, Appl. Energy 102 (2013) 885–897.
[6] G.L. Plett, Dual and joint EKF for simultaneous SOC and SOH estimation, Proc. 21st Electric Vehicle Symposium (EVS21), 2005, pp. 1–12.
[7] M. Wohlfahrt-Mehrens, C. Vogler, J. Garche, Aging mechanisms of lithium cathode materials, J. Power Sources 127 (2004) 58–64.
[8] R. Fu, S.Y. Choe, V. Agubra, J. Fergus, Modeling of degradation effects considering side reactions for a pouch type Li-ion polymer battery with carbon anode, J. Power Sources 261 (2014) 120–135.
[9] Y. Zhang, C.-Y. Wang, Cycle-life characterization of automotive lithium-ion batteries with $LiNiO_2$ cathode, J. Electrochem. Soc. 156 (2009) A527.
[10] T.Q. Duong, USABC and PNGV Test Procedures, J. Power Sources 89 (2000) 244–248.
[11] R. Mingant, J. Bernard, V. Sauvant Moynot, A. Delaille, S. Mailley, J.-L. Hognon, et al., EIS measurements for determining the SoC and SoH of Li-ion batteries, ECS Trans 33 (2011) 41–53.
[12] J. Cannarella, C.B. Arnold, State of health and charge measurements in lithium-ion batteries using mechanical stress, J. Power Sources 269 (2014) 7–14.
[13] B. Sood, M. Osterman, M. Pecht, Health monitoring of lithium-ion batteries, 2013 10th Annual IEEE Symposium on Product Compliance Engineering (ISPCE), 2013, pp. 35–40.
[14] R. Xiong, Y. Duan, J. Cao, Q. Yu, Battery and ultracapacitor in-the-loop approach to validate a real-time power management method for an all-climate electric vehicle, Appl. Energy 217 (2018) 153–165.
[15] A. Farmann, W. Waag, A. Marongiu, D. Uwe, Critical review of on-board capacity estimation techniques for lithium- ion batteries in electric and hybrid electric vehicles, J. Power Sources 281 (2015) 114–130.
[16] K.S. Ng, C.S. Moo, Y.P. Chen, Y.C. Hsieh, Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries, Appl. Energy 86 (2009) 1506–1511.
[17] C. Zhang, J. Liu, S.M. Sharkh, C. Zhang, Identification of dynamic model parameters for lithium-ion batteries used in hybrid electric vehicles, Int. Symp. Electr. Veh. 1 (2009) 1–11.
[18] M. Galeotti, L. Cinà, C. Giammanco, S. Cordiner, A. Di Carlo, Performance analysis and SOH (state of health) evaluation of lithium polymer batteries through electrochemical impedance spectroscopy, Energy 89 (2015) 678–686.
[19] D. Andre, M. Meiler, K. Steiner, H. Walz, T. Soczka-Guth, D.U. Sauer, Characterization of high-power lithium-ion batteries by electrochemical impedance spectroscopy. II: Modelling, J. Power Sources 196 (2011) 5349–5356.
[20] Y. Cui, P. Zuo, C. Du, Y. Gao, J. Yang, X. Cheng, et al., State of health diagnosis model for lithium ion batteries based on real-time impedance and open circuit voltage parameters identification method, Energy 144 (2018) 647–656.
[21] R. Mingant, J. Bernard, V. Sauvant-Moynot, Towards onboard li-ion battery state-

of-health diagnosis by a virtual sensor, World Electr. Veh. J. 5 (2012) 405–411.
[22] B. ERW, B.R. Haverkort, M. Jongerden, A score function for optimizing the cycle-life of battery-powered embedded, Systems 1 (2015) 305–320.
[23] L.J. Hardwick, H. Buqa, P. Novák, Graphite surface disorder detection using in situ Raman microscopy, Solid State Ionics 177 (2006) 2801–2806.
[24] K. Maher, R. Yazami, A study of lithium ion batteries cycle aging by thermodynamics techniques, J. Power Sources 247 (2014) 527–533.
[25] M. Ouyang, Z. Chu, L. Lu, J. Li, X. Han, X. Feng, et al., Low temperature aging mechanism identification and lithium deposition in a large format lithium iron phosphate battery for different charge profiles, J. Power Sources 286 (2015) 309–320.
[26] J. Li, J. Zhang, X. Zhang, C. Yang, N. Xu, B. Xia, Study of the storage performance of a Li-ion cell at elevated temperature, Electrochim. Acta 55 (2010) 927–934.
[27] A. Eddahech, O. Briat, J.M. Vinassa, Determination of lithium-ion battery state-of-health based on constant-voltage charge phase, J. Power Sources 258 (2014) 218–227.
[28] X. Han, M. Ouyang, L. Lu, J. Li, Y. Zheng, Z. Li, A comparative study of commercial lithium ion battery cycle life in electrical vehicle : aging mechanism identi fi cation, J. Power Sources 251 (2014) 38–54.
[29] M. Dubarry, B.Y. Liaw, Identify capacity fading mechanism in a commercial LiFePO4 cell, J. Power Sources 194 (2009) 541–549.
[30] M. Dubarry, B.Y. Liaw, M.S. Chen, S.S. Chyan, K.C. Han, W.T. Sie, et al., Identifying battery aging mechanisms in large format Li ion cells, J. Power Sources 196 (2011) 3420–3425.
[31] C. Weng, Y. Cui, J. Sun, H. Peng, On-board state of health monitoring of lithium-ion batteries using incremental capacity analysis with support vector regression, J. Power Sources 235 (2013) 36–44.
[32] C. Weng, J. Sun, H. Peng, A unified open-circuit-voltage model of lithium-ion batteries for state-of-charge estimation and state-of-health monitoring, J. Power Sources 258 (2014) 228–237.
[33] Y. Li, M. Abdel-Monem, R. Gopalakrishnan, M. Berecibar, E. Nanini-Maury, N. Omar, et al., A quick on-line state of health estimation method for Li-ion battery with incremental capacity curves processed by Gaussian filter, J. Power Sources 373 (2018) 40–53.
[34] C. Weng, X. Feng, J. Sun, H. Peng, State-of-health monitoring of lithium-ion battery modules and packs via incremental capacity peak tracking, Appl. Energy 180 (2016) 360–368.
[35] J. Tian, R. Xiong, S. Member, Q. Yu, S. Member, Fractional order model based incremental capacity analysis for degradation state recognition of lithium-ion batteries, IEEE Trans Ind. ELetron. 46 (2018).
[36] L. Wang, C. Pan, L. Liu, Y. Cheng, X. Zhao, On-board state of health estimation of $LiFePO_4$battery pack through differential voltage analysis, Appl. Energy 168 (2016) 465–472.
[37] X. Han, M. Ouyang, L. Lu, J. Li, A comparative study of commercial lithium ion battery cycle life in electric vehicle : capacity loss estimation, J. Power Sources 268 (2014) 658–669.
[38] F.L. di Scalea, P. Rizzo, S. Coccia, I. Bartoli, M. Fateh, E. Viola, et al., Non-contact ultrasonic inspection of rails and signal processing for automatic defect detection and classification, Insight Non-Destr. Test Cond. Monit. 47 (2005) 346–353.
[39] T. D'Orazio, M. Leo, A. Distante, C. Guaragnella, V. Pianese, G. Cavaccini, Automatic ultrasonic inspection for internal defect detection in composite materials, NDT E Int. 41 (2008) 145–154.
[40] I. Baghdadi, O. Briat, P. Gyan, J. Michel, Electrochimica Acta State of health assessment for lithium batteries based on voltage – time relaxation measure, Electrochim. Acta 194 (2016) 461–472.
[41] A. Matasso, Identification of the Interdepedance of Aging and Internal Pressure Evolution of Commercial Li-ion Cells, PhD Dissertations University of Texas, 2014.
[42] Z. Chen, Q. Wang, The application of UKF algorithm for 18650-type lithium battery SOH estimation, Appl. Mech. Mater. 519–520 (2014) 1079–1084.
[43] Y. Zou, X. Hu, H. Ma, S.E. Li, Combined State of Charge and State of Health estimation over lithium-ion battery cell cycle lifespan for electric vehicles, J. Power Sources 273 (2015) 793–803.
[44] Wang Qiuting, Lu Yunhao, JY, State of health estimation for lithium-ion battery based on D-UKF, Int. J. Hybrid Inf. Technol. 8 (2015) 16.
[45] H. Dong, X. Jin, Y. Lou, C. Wang, Lithium-ion battery state of health monitoring and remaining useful life prediction based on support vector regression-particle filter, J. Power Sources 271 (2014) 114–123.
[46] R. Xiong, Y. Zhang, H. He, X. Zhou, M.G. Pecht, A double-scale, particle-filtering, energy state prediction algorithm for lithium-ion batteries, IEEE Trans. Ind. Electron. 65 (2017) 1526–1538.
[47] H. He, R. Xiong, H. Guo, Online estimation of model parameters and state-of-charge of LiFePO4batteries in electric vehicles, Appl. Energy 89 (2012) 413–420.
[48] G.L. Plett, Sigma-point Kalman filtering for battery management systems of LiPB-based HEV battery packs Part 2: Simultaneous state and parameter estimation, 161 (2006) 1369–1384.
[49] R. Xiong, Q.Q. Yu, L.Y. Wang, C. Lin, A novel method to obtain the open circuit voltage for the state of charge of lithium ion batteries in electric vehicles by using H infinity filter, Appl. Energy 207 (2017) 346–353.
[50] Y.H. Chiang, W.Y. Sean, J.C. Ke, Online estimation of internal resistance and open-circuit voltage of lithium-ion batteries in electric vehicles, J. Power Sources 196 (2011) 3921–3932.
[51] J. Remmlinger, M. Buchholz, M. Meiler, P. Bernreuter, K. Dietmayer, State-of-health monitoring of lithium-ion batteries in electric vehicles by on-board internalresistance estimation, J. Power Sources 196 (2011) 5357–5363.
[52] R. Xiong, F. Sun, X. Gong, C. Gao, A data-driven based adaptive state of charge estimator of lithium-ion polymer battery used in electric vehicles, Appl. Energy 113 (2014) 1421–1433.
[53] H. He, R. Xiong, H. Guo, S. Li, Comparison study on the battery models used for the energy management of batteries in electric vehicles, Energy Convers. Manag. 64 (2012) 113–121.
[54] X. Guo, L. Kang, Y. Yao, Z. Huang, W. Li, Joint estimation of the electric vehicle power battery state of charge based on the least squares method and the Kalman filter algorithm, Energies 9 (2016) 1–16.
[55] R. Yang, R. Xiong, H. He, Z. Chen, A fractional-order model-based battery external short circuit fault diagnosis approach for all-climate electric vehicles application, J. Clean. Prod. 187 (2018) 950–959.
[56] Q. Yu, R. Xiong, C. Lin, Online estimation of state-of-charge based on the H infinity and unscented kalman filters for lithium ion batteries, Energy Procedia 105 (2017) 2791–2796.
[57] Q. Yu, R. Xiong, C. Lin, W. Shen, J. Deng, Lithium-ion battery parameters and state-of-charge joint estimation based on H-infinity and unscented Kalman Filters, IEEE T. Veh. Technol. 66 (2017) 8693–8701.
[58] J. Gao, Y. Zhang, H. He, A real-time joint estimator for model parameters and state of charge of lithium-ion batteries in electric vehicles, Energies 8 (2015) 8594–8612.
[59] R. Xiong, H. Chen, C. Wang, F. Sun, Towards a smarter hybrid energy storage system based on battery and ultracapacitor - A critical review on topology and energy management, J. Clean. Prod. 202 (2018) 1228–1240.
[60] S. Schwunk, N. Armbruster, S. Straub, J. Kehl, M. Vetter, Particle filter for state of charge and state of health estimation for lithium-iron phosphate batteries, J. Power Sources 239 (2013) 705–710.
[61] R. Xiong, F. Sun, Z. Chen, H. He, A data-driven multi-scale extended Kalman filtering based parameter and state estimation approach of lithium-ion polymer battery in electric vehicles, Appl. Energy 113 (2014) 463–476.
[62] C. Hu, B.D. Youn, J. Chung, A multiscale framework with extended Kalman filter for lithium-ion battery SOC and capacity estimation, Appl. Energy 92 (2012) 694–704.
[63] M. Ye, H. Guo, R. Xiong, H. Mu, An online model-based battery parameter and state estimation method using multi-scale dual adaptive particle filters, Energy Procedia 105 (2017) 4549–4554.
[64] Y. Hua, A. Cordoba-Arenas, N. Warner, G. Rizzoni, A multi time-scale state-of-charge and state-of-health estimation framework using nonlinear predictive filter for lithium-ion battery pack with passive balance control, J. Power Sources 280 (2015) 293–312.
[65] X. Tang, X. Mao, J. Lin, B. Koch, Capacity estimation for Li-ion batteries, Am. Control Conf. (ACC), 2011, 2011, pp. 947–952.
[66] J.T.B.A. Kessels, B. Rosca, H.J. Bergveld, P.P.J. Van Den Bosch, On-line battery identification for electric driving range prediction, 2011 IEEE Veh Power Propuls Conf VPPC 2011, 2011, pp. 0–5.
[67] M. Einhorn, F.V. Conte, C. Kral, J. Fleig, A method for online capacity estimation of lithium ion battery cells using the state of charge and the transferred charge, 2010 IEEE Int Conf Sustain Energy Technol, 2010, pp. 1–6.
[68] Z. Ma, Z. Wang, R. Xiong, J. Jiang, A mechanism identification model based state-of-health diagnosis of lithium-ion batteries for energy storage applications, J. Clean. Prod. 139 (2018) 379–390.
[69] M. Dubarry, C. Truchot, B.Y. Liaw, Synthesize battery degradation modes via a diagnostic and prognostic model, J. Power Sources 219 (2012) 204–216.
[70] M. Doyle, T.F. Fuller, J. Newman, Modeling of galvanostatic charge and discharge of the lithium/polymer/insertion cel, J. Electrochem. Soc. 140 (1993) 1526–1533.
[71] T.F. Fuller, M. Doyle, J. Newman, Simulation and optimization of the dual lithium ion insertion cell, J. Electrochem. Soc. 141 (1994) 1–10.
[72] S.K. Rahimian, S. Rayman, R.E. White, Extension of physics-based single particle model for higher charge-discharge rates, J. Power Sources 224 (2013) 180–194.
[73] N. Lotfi, J. Li, R.G. Landers, J. Park, Li-ion battery state of health estimation based on an improved single particle model, 2017 Am Control Conf, 2017, pp. 86–91.
[74] X. Han, M. Ouyang, L. Lu, J. Li, Simplification of physics-based electrochemical model for lithium ion battery on electric vehicle . Part II : Pseudo-two-dimensional model simplification and state of charge estimation, J. Power Sources 278 (2015) 814–825.
[75] K.D. Stetzel, L.L. Aldrich, M.S. Trimboli, G.L. Plett, Electrochemical state and internal variables estimation using a reduced-order physics-based model of a lithium-ion cell and an extended Kalman filter, J. Power Sources 278 (2015) 490–505.
[76] S.K. Rahimian, S. Rayman, R.E. White, Optimal charge rates for a lithium ion cell, J. Power Sources 196 (2011) 10297–10304.
[77] L. Zheng, L. Zhang, J. Zhu, G. Wang, J. Jiang, Co-estimation of state-of-charge, capacity and resistance for lithium-ion batteries based on a high-fidelity electrochemical model, Appl. Energy 180 (2016) 424–434.
[78] A. Bartlett, J. Marcicki, S. Onori, G. Rizzoni, Xiao Guang Yang, T. Miller, Model-based state of charge estimation and observability analysis of a composite electrode lithium-ion battery, 52nd IEEE Conf Decis Control, 24 2016, pp. 7791–7796.
[79] C. Zou, C. Manzie, D. Ne, Multi-time-scale observer design for state-of-charge and state-of-health of a lithium-ion battery, J. Power Sources 335 (2016) 121–130.
[80] S.J. Moura, M. Krstic, N.A. Chaturvedi, Adaptive PDE observer for battery SOC/SOH estimation, ASME 2012, Dynamic Systems and Control Conference joint with the JSME 2012 11th Motion and Vibration Conference, 2012, pp. 101–110.
[81] X. Zhou, J.L. Stein, T. Ersal, Control Engineering Practice Battery state of health monitoring by estimation of the number of cyclable, Contr. Eng. Pract. 66 (2017) 51–63.
[82] S. Dey, B. Ayalew, P. Pisu, Combined estimation of state-of-charge and state-of-health of Li-ion battery cells using SMO on electrochemical model, 13th IEEE International Workshop on Variable Structure Systems (VSS), 2014, pp. 1–6.

[83] G.K. Prasad, C.D. Rahn, Model based identification of aging parameters in lithium ion batteries, J. Power Sources 232 (2013) 79–85.
[84] J. Li, K. Adewuyi, N. Lotfi, R.G. Landers, J. Park, A single particle model with chemical/mechanical degradation physics for lithium ion battery State of Health (SOH) estimation, Appl. Energy 212 (2018) 1178–1190.
[85] R. Deshpande, M. Verbrugge, Y.-T. Cheng, J. Wang, P. Liu, Battery cycle life prediction with coupled chemical degradation and fatigue mechanics, J. Electrochem. Soc. 159 (2012) A1730–A1738.
[86] R. Xiong, J. Tian, H. Mu, C. Wang, A systematic model-based degradation behavior recognition and health monitoring method for lithium-ion batteries, Appl. Energy 207 (2017) 372–383.
[87] J. Wang, P. Liu, J. Hicks-Garner, E. Sherman, S. Soukiazian, M. Verbrugge, et al., Cycle-life model for graphite-$LiFePO_4$ cells, J. Power Sources 196 (2011) 3942–3948.
[88] M. Petit, E. Prada, V. Sauvant-Moynot, Development of an empirical aging model for Li-ion batteries and application to assess the impact of Vehicle-to-Grid strategies on battery lifetime, Appl. Energy 172 (2016) 398–407.
[89] N. Omar, M.A. Monem, Y. Firouz, J. Salminen, J. Smekens, O. Hegazy, et al., Lithium iron phosphate based battery - assessment of the aging parameters and development of cycle life model, Appl. Energy 113 (2014) 1575–1585.
[90] M. Ecker, J.B. Gerschler, J. Vogel, S. Käbitz, F. Hust, P. Dechent, et al., Development of a lifetime prediction model for lithium-ion batteries based on extended accelerated aging test data, J. Power Sources 215 (2012) 248–257.
[91] Z. Li, L. Lu, M. Ouyang, Y. Xiao, Modeling the capacity degradation of $LiFePO_4$/graphite batteries based on stress coupling analysis, J. Power Sources 196 (2011) 9757–9766.
[92] R.B. Wright, C.G. Motloch, J.R. Belt, J.P. Christophersen, C.D. Ho, R.A. Richardson, et al., Calendar- and cycle-life studies of advanced technology development program generation 1 lithium-ion batteries, J. Power Sources 110 (2002) 445–470.
[93] J. Schmalstieg, S. Käbitz, M. Ecker, D.U. Sauer, A holistic aging model for Li $(NiMnCo)O_2$ based 18650 lithium-ion batteries, J. Power Sources 257 (2014) 325–334.
[94] I. Baghdadi, O. Briat, J.Y. Delétage, P. Gyan, J.M. Vinassa, Lithium battery aging model based on Dakin's degradation approach, J. Power Sources 325 (2016) 273–285.
[95] R. Yang, R. Xiong, H. He, H. Mu, C. Wang, A novel method on estimating the degradation and state of charge of lithium-ion batteries used for electrical vehicles, Appl. Energy 207 (2017) 336–345.
[96] Z. Chen, C.C. Mi, Y. Fu, J. Xu, X. Gong, Online battery state of health estimation based on Genetic Algorithm for electric and hybrid vehicle applications, J. Power Sources 240 (2013) 184–192.
[97] J.C. Forman, S.J. Moura, J.L. Stein, H.K. Fathy, Genetic identification and Fisher identifiability analysis of the Doyle-Fuller-Newman model from experimental cycling of a $LiFePO_4$ cell, J. Power Sources 210 (2012) 263–275.
[98] L. Zhang, L. Wang, C. Lyu, J. Li, J. Zheng, Non-destructive analysis of degradation mechanisms in cycle-aged graphite/$LiCoO_2$ batteries, Energies 7 (2014) 6282–6305.
[99] R. Xiong, L. Li, Z. Li, Q. Yu, H. Mu, An electrochemical model based degradation state identification method of Lithium-ion battery for all-climate electric vehicles application, Appl. Energy 219 (2018) 264–275.
[100] M. Kallas, P. Honeine, C. Richard, C. Francis, H. Amoud, Non-negative pre-image in machine learning for pattern recognition, 19th European Signal Processing Conference (EUSIPCO 2011), 2011, pp. 931–935.
[101] S. Birla, K. Kohli, A. Dutta, Machine learning on imbalanced data in credit risk, 7th IEEE Annual Information Technology, Electronics and Mobile Communication Conference (IEEE IEMCON), 2016, pp. 1–6.
[102] R.C. Deo, Basic Science for Clinicians, Circulation 132 (2015) 1920–1930.
[103] D. Andre, C. Appel, T. Soczka-Guth, D. Uwe, Advanced mathematical methods of SOC and SOH estimation for lithium-ion batteries, J. Power Sources 224 (2013) 20–27.
[104] V. Klass, M. Behm, G. Lindbergh, A support vector machine-based state-of-health estimation method for lithium-ion batteries under electric vehicle operation, J. Power Sources 270 (2014) 262–272.
[105] A. Nuhic, T. Terzimehic, T. Soczka-Guth, M. Buchholz, K. Dietmayer, Health diagnosis and remaining useful life prognostics of lithium-ion batteries using data-driven methods, J. Power Sources 239 (2013) 680–688.
[106] Z. Wang, J. Ma, L. Zhang, State-of-Health estimation for lithium-ion batteries based on the multi-island genetic algorithm and the Gaussian process regression, IEEE Access 5 (2017) 21286–21295.
[107] A. Eddahech, O. Briat, N. Bertrand, J.Y. Delétage, J.M. Vinassa, Behavior and state-of-health monitoring of Li-ion batteries using impedance spectroscopy and recurrent neural networks, Int. J. Electr. Power Energy Syst. 42 (2012) 487–494.
[108] G. Bai, P. Wang, C. Hu, M. Pecht, A generic model-free approach for lithium-ion battery health management, Appl. Energy 135 (2014) 247–260.
[109] You G. won, S. Park, D. Oh, Real-time state-of-health estimation for electric vehicle batteries: a data-driven approach, Appl. Energy 176 (2016) 92–103.
[110] M. Zhu, S. Member, W. Hu, N.C. Kar, S. Member, The SOH estimation of $LiFePO_4$ battery bbased on internal resistance with Grey Markov chain, 2016 IEEE Transportation Electrification Conference and Expo (ITEC), 2016, pp. 1–6.
[111] R. Xiong, J. Cao, Q. Yu, Reinforcement learning-based real-time power management for hybrid energy storage system in the plug-in hybrid electric vehicle, Appl. Energy 211 (2018) 538–548.
[112] P. Singh, R. Vinjamuri, X. Wang, D. Reisner, Fuzzy logic modeling of EIS measurements on lithium-ion batteries, Electrochim. Acta 51 (2006) 1673–1679.
[113] A. Zenati, P. Desprez, H. Razik, A. Daney, U. Lyon De, U. Lyon, et al., Estimation of the SOC and the SOH of Li-ion Batteries, by Combining Impedance Measurements with the Fuzzy Logic Inference, 36th Annual Conference of the IEEE Industrial-Electronics-Society (IECON), 2010, pp. 1773–1778.
[114] R. Xiong, Y. Zhang, J. Wang, H. He, S. Peng, M. Pecht, Lithium-ion battery health prognosis based on a real battery management system used in electric vehicles, IEEE T. Veh. Technol. (2018), https://doi.org/10.1109/TVT.2018.2864688.
[115] Y. Zhang, R. Xiong, H. He, M. Pecht, Lithium-ion battery remaining useful life prediction with Box-Cox transformation and Monte Carlo simulation, IEEE Trans. Ind. Electron. 46 (2018).
[116] W. Chen, J. Zhuang, W. Yu, Z. Wang, Measuring complexity using FuzzyEn , ApEn , and SampEn, Med. Eng. Phys. 31 (2009) 61–68.
[117] Y. Kumar, M.L. Dewal, Complexity measures for normal and epileptic EEG signals using ApEn, Int. J. Comput. Commun. Technol. 2 (2011) 6–12.
[118] J.S. Richman, J. Randall Moorman, Physiological time-series analysis using approximate entropy and sample entropy, Am. J. Physiol. Hear Circ. Physiol. 278 (2000) H2039–H2049.
[119] A. Widodo, M.C. Shim, W. Caesarendra, B.S. Yang, Intelligent prognostics for battery health monitoring based on sample entropy, Expert Syst. Appl. 38 (2011) 11763–11769.
[120] H. Han, H. Xu, Z. Yuan, Y. Shen, A new SOH prediction model for lithium-ion battery for electric vehicles, 2014 17th Int Conf Electr Mach Syst, 2014, pp. 997–1002.
[121] J. Li, C. Lyu, L. Wang, L. Zhang, C. Li, Remaining capacity estimation of Li-ion batteries based on temperature sample entropy and particle filter, J. Power Sources 268 (2014) 895–903.