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REVIEW

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Review on Lithium-ion Battery PHM from the Perspective of Key PHM Steps

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Abstract

Prognostics and health management (PHM) has gotten considerable attention in the background of Industry 4.0. Battery PHM contributes to the reliable and safe operation of electric devices. Nevertheless, relevant reviews are still continuously updated over time. In this paper, we browsed extensive literature related to battery PHM from 2018 to 2023 and summarized advances in battery PHM field, including battery testing and public datasets, fault diagnosis and prediction methods, health status estimation and health management methods. The last topic includes state of health estimation methods, remaining useful life prediction methods and predictive maintenance methods. Each of these categories is introduced and discussed in details. Based on this survey, we accordingly discuss challenges left to battery PHM, and provide future research opportunities. This research systematically reviews recent research about battery PHM from the perspective of key PHM steps and provide some valuable prospects for researchers and practitioners.

Keywords Lithium-ion batteries, Prognostics and health management, Remaining useful life, State of health, Predictive maintenance

1 Introduction

Technological advances and developments of engineering industry bring more elaborate and complex devices in the Fourth Industrial Revolution, also known as Industry 4.0. Reliability and safety become particularly important during operation. However, traditional fault diagnosis and maintenance strategies can not satisfy needs for new-generation equipment. Exploring a precise, efficient, intelligent reliability technology is urgently required [1]. Therefore, prognostics and health management (PHM) came into existence in 1990s, and rapidly gained extensive attention from various countries [2]. PHM gradually developed to be systematical and normative, from built-in testing (BIT) to advanced comprehensive diagnosis systems. Nowadays, PHM mainly contains health monitoring and health management, including health state detection, remaining life prediction, maintenance optimization [3, 4].

The objectives of PHM are maintaining normal operation, reducing failures and maintenance costs, improving production efficiency, etc. To achieve the aforementioned goals, pivotal steps of PHM are: (1) Data acquisition; (2) signal processing; (3) condition monitoring; (4) health assessment; (5) failure prediction; (6) support and maintenance decision [5]. The first step is the most fundamental one, information held in data can help researchers construct models and better understand states of devices. Data types are varied, such as vibration signals, sound waves, velocity, temperature, voltage. Signal processing technique is capable of digging for useful messages hidden in noisy data. As for different signal features, signal processing methods are different. Based on requirements,

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the latter four steps can be selected. Many researchers have proposed corresponding estimation or prediction methods [6–8]. It is noted that understanding the mechanism of devices is quite useful in PHM research. According to several processes, we can see that PHM gets involved in many areas, such as sensor systems, failure mechanisms and algorithm designs. The implementation of PHM is a complicated course.

Difficulties of making PHM come true are from many aspects. Firstly, it is related to integrated subjects so that multi-source supports are needed. Some steps of PHM are tightly linked, researchers in different areas need close cooperation and share their specialized knowledge. Next, data acquisition is a tough task in a development phase of PHM. Obviously, data are valuable and necessary for model training and method verification, especially failure data and aging data. Collecting operating data or experimental data is highly time-consuming and money-consuming. The era of big data also sets a great demand on quantity and quality of data. Then, from theoretical algorithms to onboard applications, there is a long way to go. Real situations are more complicated and uncertain than determined laboratory testing environments, whether a designed PHM system can adapt a real environment should be discussed.

Despite of these difficulties, some PHM systems have been worldwide launched. PHM has been involved in many fields, such as spacecraft, helicopter, aero-engine, wind turbine, electric power, petrochemicals, etc. Nowadays, PHM has risen to new heights with a development of artificial intelligence (AI) and sensor techniques. In the military field, a set of PHM systems were deployed on F-35 fighter and practice proved strengths of PHM in reducing maintenance costs. Besides, reusable launch vehicle (RLV), F-22, EF-2000, etc., also applied PHM related techniques [9]. Integrated vehicle health management (IVHM) [10] center was founded by the Cranfield University and known enterprises like Boeing, etc. It was devoted to integrating a framework to assess current or upcoming system states and better manage system health.

Battery PHM [11] is an emerging topic as battery becomes mainstream energy storage components in decades. Batteries are widely used in modern equipment due to high-energy density, environmental friendliness and light weight, especially lithium-ion batteries. There are quantities of electronic devices such as smartphones, electric vehicles (EV), unmanned aerial vehicles, and energy storage systems. As a driven power, batteries are the most significant components in electronic equipment, thus battery health conditions directly determine whether devices properly operate. Battery-driven electronic equipment tends to be complicated because it is related to electrochemistry, electricity, and even mechanics. Similarly, battery PHM includes health state estimation and prediction, fault diagnosis, battery maintenance, etc. Firstly, state of health (SOH) and remaining useful life (RUL) are two highly concerned themes of battery health states [12] in the recent literature. SOH represents relative discharge capacity compared to rated capacity. In addition, battery fault diagnosis has received wider attention with frequent occurrences of EV accidents, such as thermal management [13, 14], voltage fault [15], internal short circuit detection [16]. Accurate battery fault diagnosis occupies an important place for ensuring safety and reliable operation of battery and electronic equipment. Unluckily, battery maintenance gets less attention than former themes. Battery swapping and replacement strategies are fundamental [17]. There still remains much space to explore, such as predictive maintenance [18].

Several useful and attractive review papers were published within the scope of battery PHM [19]. However, three main research gaps remain in existing review works:

(1) Most review works just focus on SOH and RUL of batteries, but neglect fault diagnosis and health management, which are incomplete and limited for battery PHM.

(2) Related literatures are dated because of rapid advances in battery PHM in recent years.

(3) Little review papers collected existing public datasets and characteristics which can provide much convenience for newcomers and ones who need method verification of related fields.

With the aforementioned gaps in existing battery PHM review papers, we systematically investigated the latest research to present valuable views. The main contributions of this work are as follows:

(1) Summarize recent six-year from 2018 to 2023 literature of battery PHM to track the progress of this field.

(2) Analyze advantages and limitations of different types of approaches proposed by scholars at home and abroad, and provide some suggestions for battery PHM methods.

(3) Review battery PHM from the perspective of key PHM steps, including fault diagnosis and health management so as to fill in previous research gaps.

(4) Collect public datasets published by known institutions and universities, and analyze characteristics of datasets for offering convenience for researchers.

(5) Challenges and prospects of battery PHM in the future are discussed.

The remaining part of this paper is organized in the following way. Firstly, battery testing methods and public datasets of batteries are introduced in Section 2, which is the basis of battery PHM. Next, two important components of battery PHM are introduced. Section 3 gives a brief overview of battery fault diagnosis and prediction. Section 4 introduces battery health states estimation and prediction methods. Finally, Section 5 provides a discussion on challenges and future research opportunities of battery PHM. The purpose of a final section is to draw conclusions.

2 Battery Testing and Public Datasets

This section explains main purposes and ways of battery testing, and then common public datasets released by various institutions are summarized for reference.

2.1 Battery Testing and Data Acquisition

From battery design to production, large amounts of tests are needed. First of all, before batteries are commercially rolled out, battery enterprises need to obtain battery performance parameters including capacity, nominal voltage, internal resistance, temperature characteristic, energy density, etc., through massive battery tests. If performance can not meet a designed expectation or contain product defects, batches of batteries should be redesigned or reproduced to improve product quality. Besides, for application clients, battery tests are essential to ensure battery functionality and satisfy full life cycle application requirements. This kind of battery tests concentrate on cycle performance assessment and useful life prediction, etc. Also, official supervision departments supervise battery industry and further set standards of commercial batteries with the help of specific battery testing results. In academic circles, researchers conduct specific accelerated tests or explore experiments on batteries for serving their research.

In order to save time and resources, battery is usually conducted by using accelerated cycle aging test that aims to increase a test stress such as increasing battery charge and discharge rate or temperature, consistent charge and discharge cycle. The accelerated cycle aging test can shorten a test period without changing battery failure mechanism and failure distribution [20], which can improve test efficiency and reduce test cost.

The most famous battery testing platforms are from the Arbin Instruments company, which is a leader in the battery testing area. Arbin's Laboratory Battery Testing has a wide series range, from cell, module to pack levels of all sizes. Charging/discharging cycle tests, electrochemical experiments, electrochemical impedance spectroscopy (EIS) tests and real-world simulations can be realized using a different type of equipment.

Contents of battery tests are abundant. According to the work of Xiong [21], battery performance tests contain three main directions: General electrical performance testing, AC impedance testing, and residual life testing. Considering academic and industrial requirements, referring to national standards about requirements and test methods for batteries, we thoroughly summarize battery testing in Figure 1. One can select appropriate battery testing based on one's requirements. In battery

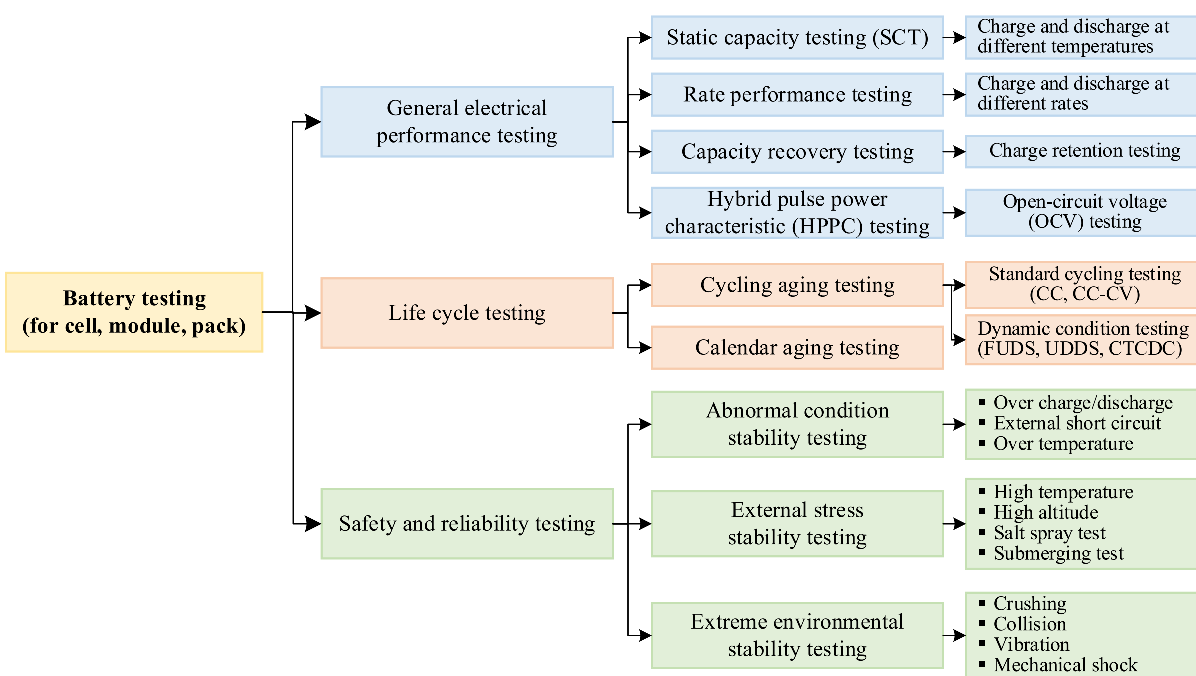

Figure 1 Review of battery testing methods

testing, many quantities can be measured, including current, voltage, capacity, EIS, etc.

For battery PHM, much attention is paid to capacity testing and life cycle testing [22]. Battery performance is tested under various conditions, such as different temperatures and discharge rates. Experimental charge/discharge policies contain constant current (CC), constant current-constant voltage (CC-CV), federal urban driving schedule (FUDS), China typical city driving cycle (CTCDC), and urban dynamometer driving schedule (UDDS). As for fault diagnosis, some fault simulation experiments are conducted so that fault data can be obtained. Generally, artificial faults are made to simulate real abnormal cases, for instance, thermal runaway, short circuit, external stress, etc. In research, accelerated life test (ALT) is a convenient approach to obtain degradation information before end of life (EOL). ALT means that batteries are continuously operated at high stresses or high rates to save time. Commonly, a failure threshold is set to 80% of an initial capacity.

Many kinds of battery tests have been conducted in academic and industrial areas, however, existing battery tests for battery PHM are not enough. There are some suggestions and perspectives on battery testing of battery PHM:

(1) In reality, lots of factors will influence testing results, such as operation conditions, environmental factors, user behaviors. Those factors are coupled with each other. How to accurately simulate complex real cases remains a question.

(2) While the ALT can accelerate test processes and provide convenience, however, whether results of ALT can represent real situations is doubtful. How to transfer ALT results to real circumstances is a valuable topic.

(3) Some battery tests are destructive, which are costly and inconvenient. Nondestructive testing and advanced sensors that can explore an internal situation of batteries are potential directions for battery PHM.

2.2 Public Datasets Collection and Analysis

There are many academic and industrial institutions publicly providing battery testing datasets, such as the center for advanced life cycle engineering (CALCE) and NASA Ames prognostics center of excellence (NASA Ames PCoE). Those datasets provide convenience for researchers in the battery PHM field. In order to facilitate scholars to conduct in-depth research, this paper sorts out some existing public datasets for scholars' reference, illustrated in Table 1.

The internal aging mechanism of rechargeable batteries is complex, and many environmental factors affect their degradation, so it is difficult to estimate and predict the health status of batteries [57]. At the same time, data that can support the research is also limited. Although this paper has sorted out some existing public data that can be used for research, there are still many deficiencies in the current era of big data:

(1) Research on battery health prediction under different operating conditions is insufficient. The performance degradation of rechargeable batteries is affected by operating conditions and environments of equipment. Degradation characteristics of rechargeable batteries may be different under different operating conditions. For example, aging trends of 25 ℃ and 40 ℃ at discharge rates of 1 C and 3 C are different. Existing health status estimation and prediction methods usually assume that working conditions are constant and fixed. Although this simplification reduces the complexity of aging modeling and prediction, it will affect the accuracy of estimation and prediction results, and cause large prediction errors in practical applications.

(2) Research on battery pack health prediction is still in its infancy. Most existing studies aimed at cell health prediction, and there are many algorithms and certain applications. In practice, battery cells are connected in series or parallel to form battery packs (pack level). States of battery packs are more complex than those of single batteries, involving mutual coupling between cells and other problems such as inconsistency of cells, electrical imbalance and temperature gradient. Its health status is not just a simple superposition between monomers, but also important for equipment to predict the health status of a battery pack. However, there is still a large gap in the research on the health status prediction of a battery pack.

(3) Most existing prediction methods remain in a theoretical stage and cannot be packaged into vehicle battery management systems (BMSs). Although most validity and accuracy of existing methods have been verified in experimental data, few actual cases are encapsulated into BMSs. In addition, how to verify the accuracy of prediction results after encapsulation into BMSs remains to be discussed. Most existing methods are not adaptable and they are only used for a certain battery or a certain operating environment.

(4) Inadequate battery aging data sets. In the research process, the lack of battery aging data under multiple working conditions and scales, the lack of battery pack data and the lack of battery actual operation data, etc., have also caused some difficulties in the research on battery health condition prediction. Extreme temperature conditions will influence battery aging. More battery datasets at high or low temperatures are needed. Most existing studies use data collected in laboratory, however, there are few studies on data in practical applications.

Table 1 Battery public datasets information collection

Institutions	Battery specification and data quantity	Charge/discharge policy	Other environmental conditions	Characteristics	Relative works
Stanford University & MIT [23, 24]	240 phosphate (LFP)/graphite cells Type: A123 (ANR26650M1A) Nominal capacity of 1.1 A·h Nominal voltage of 3.3 V	Charge by multi-step CC-CV protocols Discharge at 4 C	Test in a temperature chamber set to 30 °C	Use 224 multi-step, ten-minute fast-charging protocols Can be used in fast charging research	[25–29]
	124 phosphate (LFP)/graphite cells Type: A123 (ANR26650M1A) Nominal capacity of 1.1 A·h Nominal voltage of 3.3 V	Charge by CC-CV protocols Discharge at 4 C	Test in a temperature chamber set to 30 °C	Charged with a one-step or two-step fast-charging policy Can be used in fast charging research	
CALCE [30]	Type: INR 18650-20R Phosphate (LNMC)/graphite cell Nominal capacity of 2000 mA·h	Low current OCV test (e.g., C/20, C/25) Incremental OCV test Dynamic profile test	Test at various temperatures (0 ℃, 25 ℃, 45 ℃)	Can be used in the SOC estimation of Li-ion Include dynamic tests (e.g., FUDS)	[31–33]
	phosphate (LFP)/graphite cell Type: A123 (ANR26650M1A) Nominal capacity of 2230 mA·h	Low current OCV test Dynamic profile test	Temperature ranging from 0 °C to 50 °C with interval of 10 °C	Can be used to study the effect of temperature to OCV-SOC Test under DST and FUDS	[33, 34]
	15 $LiCoO_2$/graphite cells (CS2) Nominal capacity of 1100 mA·h	Charge by CC-CV protocols Discharged at a constant current	Test in an Arbin LBT200 equipment	Can be used in RUL prediction research	[30, 35–37]
	12 $LiCoO_2$/graphite cells (CX2) Nominal capacity of 1350 mA·h	Charge by CC-CV protocols Discharged at a constant current	Test in an Arbin LBT200 equipment	Can be used in RUL prediction research	[30, 35, 38]
NASA Ames PCoE [39]	About 40 18650 Li-ion cells Nominal capacity of 1.1 A·h Nominal voltage of 3.3 V	Charge by CC-CV protocols Discharge at a constant current	Test at room temperature	Include EIS tests sweeping from 0.1 Hz to 5 kHz	[40–45]
	About 28 18650 Li-ion cells Nominal capacity of 1.1 A·h Nominal voltage of 3.3 V	Random walk (RW) discharging (current loads ranging from 0.5 A to 5 A) 7 various experimental settings	Test at various temperatures (25 ℃, or 40 ℃)	Extend research under random walk discharging policy	[45–47]
Oxford University [28]	12 NCR18650BD (NCA/graphite) cells Nominal capacity of 3 A·h	Charge by CC-CV protocols (C/2, C/4)	Test at room temperature (24 ℃)	Combination of cycle cyclic and calendar aging Test under joint loads Include EIS tests	[48]
	8 kokam (SLPB533459H4) Li-ion pouch cells Nominal capacity of 740 mA·h	Charge by CC-CV protocols Cells discharge at urban Artemis profiles	Test in a thermal chamber at 40 ℃	Long-term aging tests	[49–51]

Table 1 (continued)

Institutions	Battery specification and data quantity	Charge/discharge policy	Other environmental conditions	Characteristics	Relative works
Mendeley	18650 PF Li-ion battery (panasonic) Nominal capacity of 2.9 A·h	Charge by CC-CV protocols	Test at 5 temperatures (−20 ℃~25 ℃)	HPPC, drive cycles, and EIS tests	[52–54]
	4 cylindrical lithium-ion cell types: 18650-HB6 (LG), NCR18650B (panasonic), IFR18650 (ShenZhen), IMR18650 (Efest).	Charge by CC-CV protocols Constant power discharge	Test at constant temperature (25±0.5 ℃)	Can be used in studying correlation between discharge duration and discharge power	[55]
Cavendish Laboratory	12 $LiCoO_2$/ graphite cells (Eunicell LR2032) Nominal capacity of 45 mA·h	Charge by CC-CV protocols Discharge at 2 C-rate	Test at constant temperatures (25 ℃, 35 ℃, 45 ℃)	Test EIS and charge-discharge cycles at different temperatures and SOC points	[56]

Although there are some publicly available data sets to researchers, there are still large data gaps.

3 Battery Fault Diagnosis and Prediction

After obtaining battery data by testing, battery states can be monitored, and the aim of this monitoring is to timely detect battery faults and further predict potential faults to ensure normal operation of systems. In this section, classification of battery faults is firstly introduced in Section 3.1, and aiming at these different types of battery faults, battery fault diagnosis and prediction methods are briefly reviewed in Section 3.2.

3.1 Classification of Battery Faults

Multiple battery faults affect battery usage safety [58], such as overcharge fault, accelerated degradation, connection fault. In this section, battery faults are briefly divided into three categories: (1) External battery faults; (2) internal battery faults; (3) battery thermal runaway. Classification of battery faults is shown in Figure 2.

3.1.1 External Battery Faults

External battery faults may influence normal abilities of BMS and even cause internal battery cell-level faults. This kind of faults are mainly caused by abnormal operation of electronic components outside batteries.

External battery faults include: (1) Sensor faults, containing current, voltage and temperature sensor faults; (2) heating and cooling system faults; (3) controller area network (CAN) communication faults and electric relay faults; (4) cell connection faults such as contact oxidation and looseness.

3.1.2 Internal Battery Faults

Compared with an external failure of a battery, the inducement of internal faults of the battery is more difficult to judge because the battery internal reaction process during operation is unclear.

The main causes of battery internal faults include: (1) Defects in manufacturing process; (2) overcharge and over-discharge; (3) overheating; (4) internal short circuit and micro short circuit; (5) accelerated degradation.

3.1.3 Battery Thermal Runaway

Thermal runaway (TR) is the most serious type of battery faults, which directly threatens the life safety of users. TR is usually induced by battery electrical faults and battery internal faults. Many scholars have been donated to TR mechanisms and some side reactions have been modeled when a battery is thermally out of control. In addition, the process of thermal runaway is usually accompanied by spontaneous heat production and side reactions, mainly including (1) SEI decomposition; (2) anode electrolyte; (3) cathode decomposition; (4) electrolyte decomposition; (5) short circuit and so on. The main cases of the TR can be divided into 3 types: (1) Mechanical abuse; (2) electrical abuse; (3) thermal abuse. Detailed classifications are illustrated in Figure 2.

3.2 Battery Fault Diagnosis and Prediction Methods

Based on analysis of battery faults classifications in Section 3.1, this section mainly introduces battery fault diagnosis and prediction methods. Fault diagnosis algorithms can be divided into: (1) Model and experiment based methods; (2) data-driven methods. Details can be found in Figure 3. Data-driven methods are popular nowadays due to their flexibility and simplicity, while model and

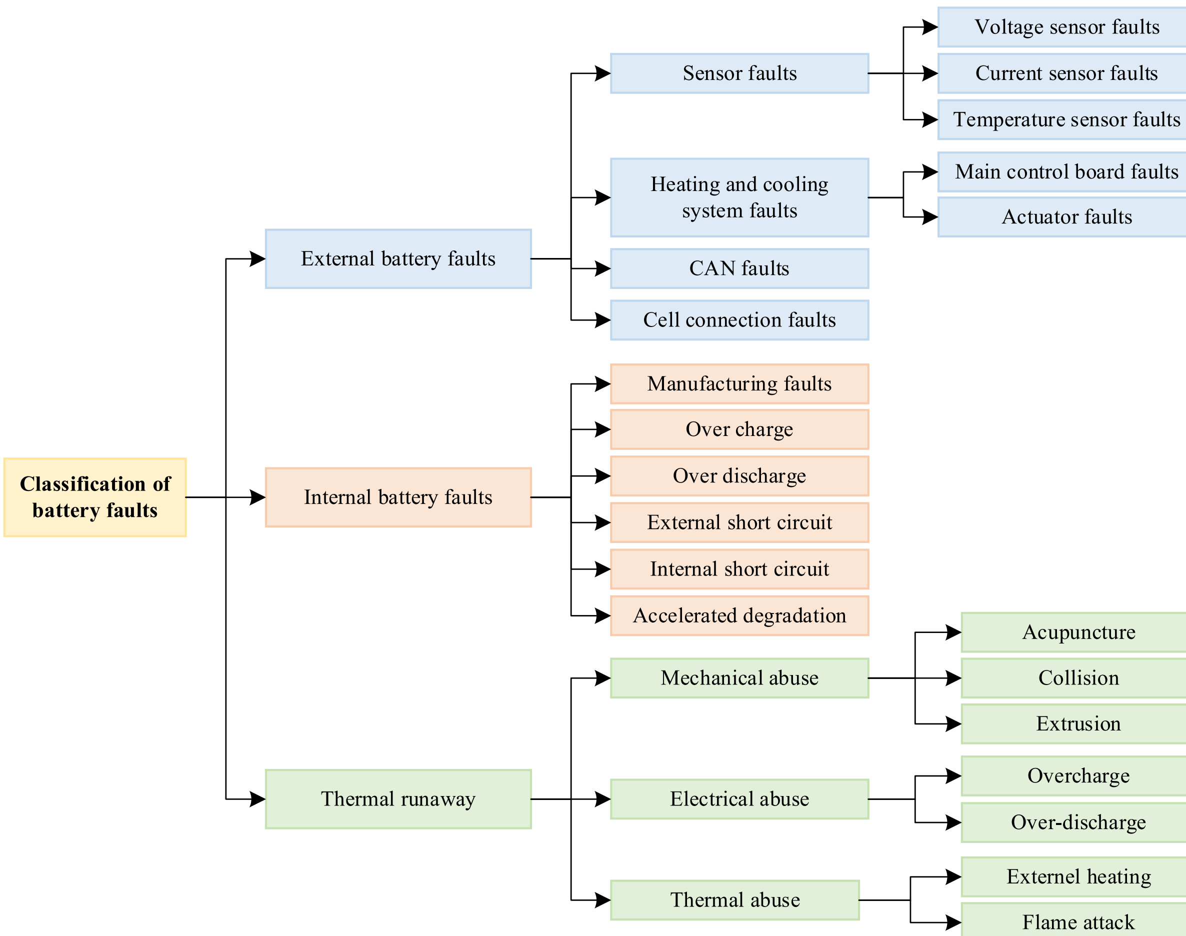

Figure 2 Classification of battery faults

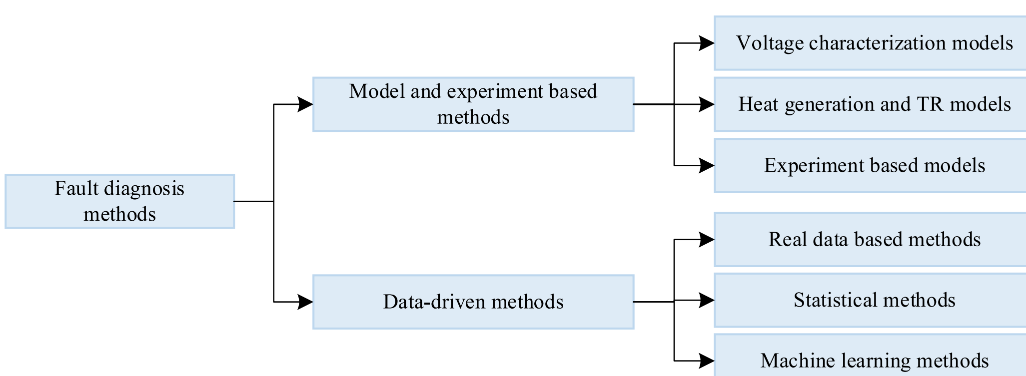

Figure 3 Battery fault diagnosis and prediction methods

experiment based methods have higher requirements for physical knowledge. If enough data are available, data-driven methods are fine choices for effectively realizing battery fault diagnosis. However, battery fault data are difficult to obtain sometimes, model and experiment based methods can deal with the situation in which there lacks battery data.

3.2.1 Model and Experiment Based Fault Diagnosis Methods

Model-based fault diagnosis methods are conducted based on mechanism models to describe electrical and thermal characteristics of a battery in the process of use, such as electrochemical models, thermal models and thermoelectric coupling models. Usually, based on the prior knowledge of a model structure, state estimation and parameter identification methods are used to observe a key state and parameter information of a battery from battery data. These observed values are used to conclude whether a battery has failed.

(1) Battery voltage characterization models

Nowadays, the research on lithium-ion battery modeling in a normal state is much more extensive. Equivalent circuit modeling [59], fractional-order modeling [60], electrochemical modeling [61], and their simplification, on-line and off-line parameter estimation have been widely studied. Wei et al. [62] analyzed some critical values of voltage and temperature when a real vehicle thermal runaway occurs, and traces a cause. In Ref. [63], SOC and ohmic resistance of a battery were estimated by using extended Kalman filter (EKF) and recursive least squares with a forgetting factor, and a fault level of internal short circuit was determined by combining the voltage and temperature of a battery. Based on current and voltage data, Refs. [64, 65] carried out parameter identification and state estimation for a battery system model (an electrochemical model and an equivalent circuit model), and judged whether a battery failed through the analysis of time-varying parameters. Liu et al. [66] used EKF to detect and isolate sensor faults.

(2) Heat generation and TR models

In addition to using models to describe battery voltage performance, a heat generation model of lithium-ion batteries was also very important because it is needed to compute a temperature rise of a battery under abnormal conditions. A thermal model was divided into lumped model [67], 1-D model [68], 2-D model [69], 3-D model [70]. The accuracy of models gradually increases. The heat generated by a battery is mainly composed of ohmic heat, polarization heat, reaction heat, contact resistance heat and side reaction heat. The aforementioned heat generation is calculated through an electrochemical model, then they are input into a battery transformer equation to obtain a battery temperature rise. Some changes of electrochemical parameters were obtained by the Arrhenius equation, and an electrochemical equation was introduced to realize the coupling of electrochemical model and thermal model [71].

Meanwhile, some models can evaluate the possibility of side effects and TR of a battery based on battery use and heat generation processes. In Ref. [72], electrochemical characteristics and thermal characteristics of a battery were coupled, and a prediction model of thermal runaway in a high-temperature environment was established for high-capacity lithium-ion battery. In Ref. [73], based on an electrochemical thermal coupling relationship, a prediction model of thermal runaway caused by short circuits in lithium-ion battery was established. Meanwhile, the boundary of TR was determined according to different heat source intensities and durations, which was distinguished from a safety zone. Feng et al. [74] established a lithium-ion battery TR prediction model and described temperature and voltages changes of lithium-ion cells during thermal runaway for heat abuse.

(3) Experiment based methods

In addition to model-based methods, experiments are an important part in battery fault diagnosis. In the industry area, some basic battery safety tests such as heating, acupuncture, collision were conducted in order to achieve abnormal data such as voltage, gas and expansion force [75, 76]. Chen et al. [77] used experiment data of an external short circuit fault of battery cells based on random forest algorithm, meanwhile, the leakage of a battery was analyzed. The experimental method studied the performance of current and voltage under specific fault conditions, and can usually get good conclusions, but it is not exactly same as an actual fault.

3.2.2 Data-Driven Fault Diagnosis Methods

Data-driven fault diagnosis methods use data to detect abnormal states of battery. This kind of methods depend on a large amount of data. For example, voltage anomaly usually indicates deeper internal faults, such as internal short circuit and structural faults, which can be analyzed by data-driven methods including real data analysis methods, statistical methods, machine learning methods.

(1) Real data analysis methods

This kind of methods rely on battery data measured by sensors. In a lithium-ion battery pack, temperature sensor, voltage sensor, and current sensor can collect cell information and these data are uploaded to BMS. Due to limitation of fault labels and data quality, methods based on real data usually focus on the setting of thresholds and heuristic rules of voltage and temperature representation.

Gao et al. [62] analyzed a thermal runaway process of a battery and some key time nodes of a thermal runaway instance, such as an abnormal starting point of voltage and temperature. In addition to setting of basic thresholds, Sun et al. [78] online estimated temperature of lithium-ion battery using Kalman filter (KF) based on real data. Xia et al. [79] extended a way of battery faults diagnosis to external short circuit. Hinton et al. [80] proposed a novel fault diagnosis method using feature fusion and manifold learning for dimensionality reduction, and finally identified abnormal signal features based on a clustering-based outliners point detection method. Kang et al. [81] proposed a multi-fault diagnostic method using voltage measurements and topology technology, and diagnosed various faults including short circuit, sensor faults, etc. Li et al. [82] adopted a circuit faults detection approach based on weighted Pearson correlation coefficient and considered forgetting factor to avoid misdiagnosis.

(2) Statistical methods

Apart from directly diagnosing faults according to real data, statistical methods can be used to analyze the abnormal representation of a battery, so as to realize fault diagnosis of the battery. Inconsistent temperature [83] and abnormal aging state of battery cells will usually lead to inconsistent voltage of cells. The method based on statistics has a good ability to detect the inconsistency of each characteristic quantity of each monomer of a battery pack.

Zhang et al. [84] explored various entropy algorithms to diagnose a battery real-scenario fault, and designed a multi-level diagnosis strategy for actual vehicle fault diagnosis. Wang et al. [85] proposed a voltage anomaly detection method based on a modified Shannon entropy, and compared the similarities and differences between Shannon entropy and sample entropy in fault diagnosis. Wu et al. [86] combined Hausdorff distance and modified Z-score to conduct online fault detection and location for battery pack. Xia et al. [87] used a sliding window to directly calculate the correlation coefficient between fixed-length segment voltages to analyze the inconsistency between voltage values.

(3) Machine learning methods

Machine learning methods are more and more attracted and popular these years. When having battery sensor sequences and faults, it seems to be the most direct and effective way to use machine learning methods to establish a discrimination model to find fault information. However, machine learning methods face with problems of lacking data, unreliable labels and poor generation performance under an actual using scenarios, which need to be solved.

Many scholars try to use machine learning methods to automatically capture characteristics of battery faults and TR. Xie et al. [88] constructed a novel convolutional neural network (CNN)-based diagnostic framework for series battery packs to realize fault type inference and fault grade evaluation. Signal imaging techniques were used to analyze detailed system states. Li et al. [89] proposed a density-based spatial clustering of applications with noise (DBSCAN) based method to analyze 2D fault features. The effectiveness of the algorithm was verified and tested on real vehicle data. In addition to clustering-based methods, a symbolism-based method such as fuzzy logic can effectively identify faults [90]. With the help of neural networks, a normal working mode of a battery was easy to learn. Hong et al. [91] used a long short-term memory (LSTM) model to predict voltage in a few steps as a normal battery output, which was compared with real voltage. Then, a threshold-based rule was proposed to assert battery faults. With a development of deep learning, a meta-learning method was proposed in Ref. [92], which learned the similarity of battery observable data before TR including current, voltage, temperature and so on. It should be noted that through an ablation experiment, thermal imaging makes a great contribution to the accuracy of the model. Thus, due to cost reasons, this method can not be applied to real vehicles.

For battery fault diagnosis, more efforts should be put in fault pre-detection and warn in advance. Fault pre-detection is significant for ensuring the safety of battery system and users. Tense diagnosis strategies are needed at any situations for security.

4 Battery Health Status Estimation and Health Management

With an increase of usage time, battery will gradually degrade and aging. Different from battery faults, battery degradation is a slow and long-term process so health states should be estimated during using. In this section, we firstly review popular SOH and RUL methods based on the latest literature; then a brief summary of predictive maintenance progress is given.

4.1 State of Health Estimation Methods

SOH and RUL are the most important metrics for evaluating batteries in PHM. For SOH, it is used to represent a health degradation degree of a battery during its service period. It is usually evaluated by an internal resistance of a battery or discharge capacity. It reflects the health state of the battery and its ability to output power. RUL is used to represent remaining useful life or the number of charge-discharge cycles until a battery reaches a preset threshold by system manufacturers or users. RUL prediction is a necessary condition to ensure the safe

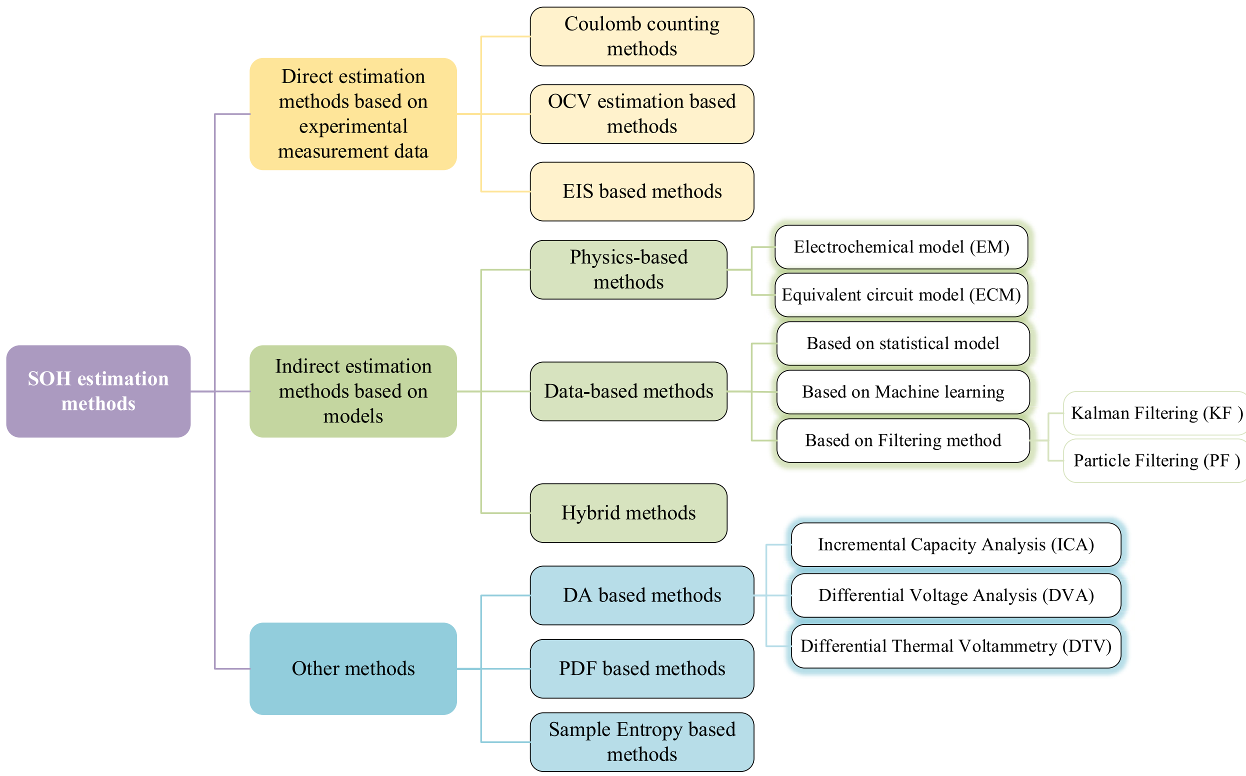

Figure 4 Classification of SOH estimation methods

and reliable operation of a battery system [93]. In order to prevent premature performance degradation and catastrophic failures, continuous monitoring and control are required during battery life. Therefore, accurate prediction of battery SOH and RUL is required to ensure the safe operation of a battery system and its energy supply equipment.

4.1.1 Data-Driven Methods

SOH is used to represent aging degradation of a battery and many characterization methods can represent it. For example, the capacity, resistance, and power of batteries can be used as the characterization parameters of SOH [94]. The ratio of the current maximum available capacity to the nominal capacity of a battery can be used to represent SOH.

$$SOH_Q = \frac{Q_{current}}{Q_{nominal}}, \tag{1}$$

where $Q_{current}$ represents the currently available battery capacity. $Q_{nominal}$ is the nominal capacity, it is measured under standard conditions and it is determined once a battery is produced.

There are a variety of SOH estimation methods according to different classification standards [95, 96]. A relatively comprehensive classification method is introduced here. SOH estimation methods can be mainly divided into three categories. Direct estimation methods based on experimental measurement data, indirect estimation methods based on models and other methods. Each category can be subdivided into many sub-categories according to different characteristics of methods. Such as indirect estimation methods based on models including physics-based methods, data-based methods, and hybrid methods. SOH classification of estimation methods is shown in Figure 4.

Direct SOH estimation methods based on experimental measurement data are mainly carried out in laboratory environments. Directly using capacity tests, impedance tests, or other testing methods to obtain battery SOH. The following details several classical direct estimation methods.

(1) Ampere-hour integral method

Ampere-hour integral method (AH), also be known as the Coulomb counting method, is a basic traditional method. It calculates the integral of discharge current against time to determine the total discharge power of the battery under the condition of complete discharge, and then the ratio of it to the nominal capacity of a battery can be expressed as SOH. This method is often used to estimate the SOC. Zhang et al. [97] proposed a data-driven Coulomb counting method. They converted a traditional IC curve into a SOC based IC curve based on incremental capacity analysis (ICA). After correcting an initial SOC error, four voltage values were selected as an input of a Gaussian process regression (GPR) model to achieve actual capacity estimation.

(2) Open-circuit-voltage (OCV) estimation methods

OCV estimation methods obtain the relationship between SOH and OCV through a large number of laboratory tests. Zhang et al. [98] proposed a new non-experimental relationship reconstruction method between OCV and SOC/SOE. An OCV-SOC curve was obtained without an additional battery test, and then SOC can be estimated based on OCV. Based on the new relationship, the error of the estimation of SOC results by an EKF was effectively reduced. Knap et al. [99] proposed a method for SOC estimation based on an untracked Kalman filter (UKF), which comprehensively considered the wide and rapidly changing temperature and other conditions. The OCV parameters of a battery were obtained by an online parameter identification method, and measured values of current and temperature were used for SOC estimation of a battery.

(3) Electrochemical impedance spectroscopy (EIS) based methods

EIS based estimation methods use a wide spectrum to estimate SOH, and EIS can also be used to estimate the parameters of an equivalent circuit model to estimate remaining capacity of a battery [100]. However, EIS measurement requires a long test time and a stable test environment, so there are difficulties in practical applications. Destructive methods refer to the use of X-ray, scanning electron microscope, or other technologies to observe changes in an internal microstructure of a battery under different aging mechanisms from the perspective of microscopic mechanisms, to research battery aging mechanisms and battery SOH [101]. This method can intuitively observe internal changes caused by battery aging. However, this method is only applicable to aging mechanism research under laboratory conditions because a battery needs to be disassembled and damaged.

To sum up, although most direct estimation methods based on experimental measurement data are difficult to implement in a complex environment of practical applications, the rich information obtained and relatively accurate SOH estimation results can provide theoretical supports and accuracy verification for model-based methods.

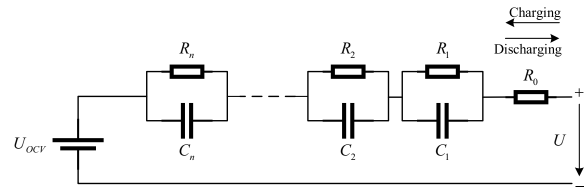

Figure 5 Schematic diagram of ECM

Indirect estimation methods based on models can be further divided into physical-based model methods, data-based methods, and other methods.

4.1.2 Physical Model Based Methods

(1) Electrochemical model estimation methods

Electrochemical model (EM) estimation methods consider complex chemical processes inside a battery [102]. Physical-based models can accurately describe degradation mechanisms, providing the degradation of knowledge without a large number of historical data. Model parameters are chemical and physical significance and then researchers can get accurate estimation results usually in the electrolyte conductivity and electrode porosity as indicators of estimating SOH. However, due to a large number of electrochemical parameters and partial differential equations involved in an EM model, it is difficult to solve and computational complexity is high. Therefore, simplifying an EM model is necessary to meet the requirements of online estimation and reduce computational pressure. A widely used simplified model is a pseudo-two-dimensional (P2D) model [103], a single-particle model (SPM) [104], etc. The higher the simplification degree is, the lower computational complexity is, but corresponding accuracy will also be reduced.

(2) Equivalent circuit model estimation methods

Equivalent circuit model (ECM) estimation methods [105] is a circuit model composed of electronic components such as resistor, capacitance, and constant voltage source, which can be used to describe external characteristics of a battery. ECM consists of resistance (R_0), voltage source (U), resistor capacitance circuits, etc. A schematic diagram of an ECM is shown in Figure 5. According to the number of resistor capacitance circuits (RC), it can be divided into a Rint model (RC = 0), a Thevenin model (RC = 1), a dual-polarization model (RC = 2), etc. According to a ECM model, the corresponding equation of state can be derived, and its parameters can be identified to provide further analysis [106]. The calculation of an ECM is relatively small, and it has been applied to SOH estimation. Wang et al. [107] used an ECM to characterize an aging phenomenon of batteries under constant voltage charging conditions, proposed a new health indicator, and used this indicator to estimate SOH online. Through correlation analysis and performance evaluation, the adaptability and effectiveness of this method were verified for health state assessment of lithium-ion batteries. However, it required some empirical parameters, and this model lacked a physical explanation. Parameters cannot be automatically updated and the accuracy is low.

Although physical-based model methods do not need a lot of historical data in a modeling process, the closer the model is to a real battery system, the more accurate the estimation results will be, and the higher the complexity will be, and the more calculation will be required. The challenges of this approach lie in trade-offs between computational complexity and model accuracy, as well as adaptability to environments.

(3) Data-based model methods

Data-based model methods are using battery data in the process of history and operation, etc., to analyze and extract useful information for the degradation of battery and estimate health state. This kind of method does not need an internal complex degradation mechanism of batteries for precise modeling and professional electrochemical knowledge, only needs data. Mainstream methods can be specifically divided into two categories. One is based on statistical model methods, the other is based on machine learning methods more popular in recent years.

(4) Statistical methods

Using statistical models, based on existing battery data characteristics, one can choose different methods to model battery degradation. Borrowing from an established model to estimate battery health. A relatively simple method is using known data to establish an experience aging model. Usually, it can be expressed as the function of cycles or time, and then with the aid of an experience model, for example, polynomial, exponential, power function which are empirical models commonly used to fit later unknown data. This method is small in computation and easy to operate, but it is highly dependent on experimental results, and the accuracy of the estimate is low, which cannot adapt to the influence of environmental changes and other emergencies. Therefore, this kind of method is often used in combination with filtering updating methods that will be introduced later. In addition, stochastic models based on a Markov process, a Gamma process, a Wiener process also found some applications in battery health state prediction. Qualitative is inevitable due to uncertainty in working environments, so stochastic models can well characterize a random degradation process. However, different random models are suitable to different data characteristics, so corresponding random models should be selected by data. Dai et al. [108] used a Markov chain and neural networks to estimate SOH. Wang et al. [109] obtained an estimation result with good robustness and accuracy with the help of an improved Brownian motion model.

(5) Machine learning based methods

With an improvement in computing levels and the rise of artificial intelligence, methods based on machine learning have attracted more and more attention [110]. Machine learning methods have good dynamic accuracy and strong learning ability. Strong nonlinear problems can also get a good effect. Steps can generally be summed up in machine learning methods to data preprocessing, feature extraction, model parameters estimation, output, etc. Feature extraction is the most critical step which will directly limit the accuracy of estimation results. In addition, the quality of training data and the consistency of test data with training data will also affect the accuracy of estimation results. The increasing development and popularity of big data platforms help machine learning to solve the problem of large data demands [111, 112]. Mature machine learning methods include artificial neural networks (ANNs), support vector machine (SVM), random forest (RF), etc. Some methods can give a confidence interval of estimation results, such as Gaussian process regression (GRP), dynamic Bayesian network (DBN), correlation vector machine (RVM). Zhang et al. [56] reduced the dimension of EIS spectrum data to low-dimensional features and used it as an input of a GPR model to predict battery health state and RUL at different temperatures. However, due to the difficulty in obtaining an EIS spectrum, this method is difficult to be applied to practical engineering.

(6) Filtering based methods

Methods based on adaptive filtering are often used in combination with an empirical model method or equivalent circuit model method, which can adaptively adjust model parameters based on new data and reduce model estimation errors. It mainly includes KF correlation methods and particle filter (PF) correlation methods [113–115]. Many researchers have proposed new adaptive filtering methods to improve estimation effects. For example, Li et al. [116] proposed a method based on the combination of a mixed Gaussian process model and

PF, which can be used to estimate SOH under uncertain conditions. Wang et al. [117] introduced a spherical volume particle filter (SCPF) to solve a state-space model. This method was widely used because of its more adaptive features. However, a main problem is that it requires a lot of training with experimental data to get the current capacity of a battery.

(7) Other methods

In recent years, researchers in this field have proposed a variety of new methods for different problems, which have obtained good estimation results, such as sample entropy-based methods.

The differential analysis (DA) method is mainly realized by differentiating a thermodynamic curve of electric power obtained by a constant current charge and discharge of batteries. This kind of method is widely used in the study of battery behavior in a laboratory environment. ICA method through a small current rate (C/25) of a battery charge and discharge corresponding dV/dQ-V analysis method. A differential voltage analysis (DVA) method was used to analyze a dQ/dV-Q relationship [95]. The peak value of the curve can be used to characterize the electrochemical process of a battery during operation. For example, an IC peak corresponds to different phase transition processes on the battery electrode, and a DV peak corresponds to the occurrence of the reaction in a single-phase solution region, so SOH estimation can be derived from the relationship between different cycle times and peak information (such as peak position and peak amplitude) [118]. Differential thermal voltammetry (DTV) estimates battery SOH through voltage, temperature, and other information [119]. Jiang et al. [118]. extracted the height characteristics of peak and valleys of curves under different cycles based on IC curves, and studied the functional relationship between characteristics and battery SOH, then made an estimation. Li et al. [42] proposed a Bayesian nonparametric method for SOH estimation of lithium batteries by extracting a health index that is highly correlated with capacity from a partial charging IC curve. Li et al. [120] proposed an ICA-based SOH estimation method for NMC lithium-ion battery, which can estimate a battery state with high precision under different cycle depths. Although ICA or DVA methods can accurately describe the reaction of physical and chemical processes. However, this method requires complete discharge under the condition of constant and small current to ensure that a peak value can be detected, and temperature will affect the accuracy of estimation, which requires smooth filtering and difficult operations.

Sample entropy can be used to quantify time series characteristics and complexity, so it can be used to characterize battery capacity loss. Li et al. [121] combined PF with sample entropy calculated by battery surface temperature to estimate capacity attenuation with a small error. Feng et al. [122] calculated battery capacity using an algorithm based on a probability density function and charge-discharge data and explored the equivalence of this method with ICA/DVA.

Accurate SOH estimation is the basis of RUL prediction, and SOH estimation accuracy directly affects RUL prediction accuracy. RUL prediction is more difficult than SOH estimation because future conditions are uncertain.

4.2 Remaining Useful Life Prediction Methods

RUL of Li-ion batteries can be defined as the difference between the end of a life point and a predicted starting point α [123], and the EOL can be calculated from Eq. (2) to be related to the pre-set failure threshold. Generally, failure occurs when the set capacity reaches 80% of its initial value.

$$\mathrm{RUL} = \mathrm{EOL} - \alpha. \tag{2}$$

Research on RUL prediction of equipment has made great progress in the past decade. Generally speaking, existing RUL methods can be divided into three categories which are model-based methods, data-driven methods, and hybrid methods. Figure 6 shows the classification of existing Li-ion battery RUL prediction methods.

Model-based methods refer to prediction of battery RUL based on aging mechanisms, material properties, the load of a battery, and other factors [124]. This method is highly dependent on the precision of modeling and the precision of model parameters. Due to the rapid development of industrial technology and increasing complexity and uncertainty of equipment, the difficulty of mechanism modeling has also increased. It is difficult to obtain an accurate mechanism model. Therefore, data-driven methods have gradually become a main research method [125]. A hybrid method combines different methods or models to predict RUL of Li-ion batteries. Its purpose lies in accurately estimating RUL of Li-ion batteries. A fusion method generally includes two kinds. One is combining model-based methods with data-driven methods. Another is the integration of different data-driven methods.

4.2.1 Data-Driven Methods for RUL Prediction

Data-driven methods use statistical theory or machine learning technology to establish a mathematical model and estimate parameters with the help of measured

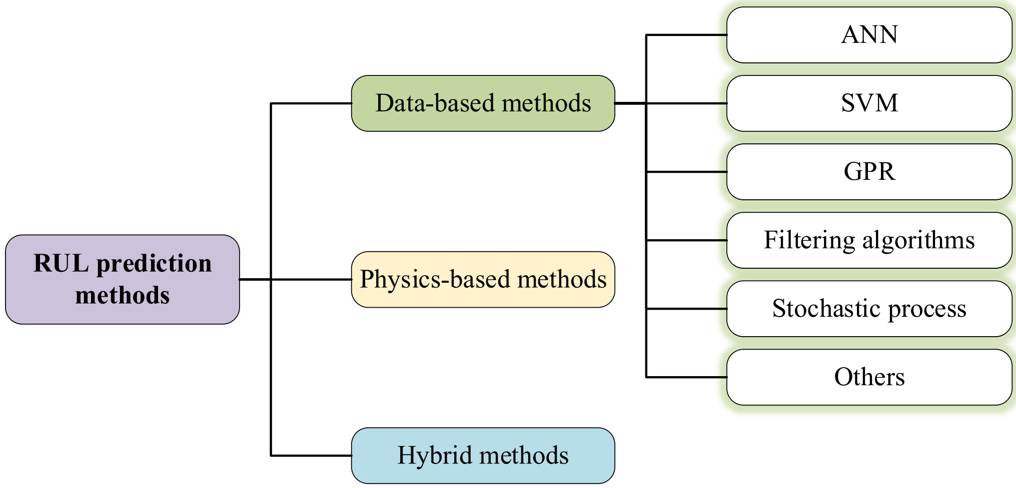

Figure 6 Classification of RUL prediction methods

data. With battery RUL or related quantity as a learning target to train a model, and learn parameters [126]. There are many common data-driven methods, such as ANNs, SVM, GRP, PF, KF, stochastic process like Wiener process.

(1) Neural networks (NN) based methods

Neural networks are a research algorithm in the field of artificial intelligence. It is a typical operation model of a nonlinear method. It is connected by a large number of nodes, and each node represents an output function. The principle of neural networks applied to RUL prediction of lithium-ion batteries is to take corresponding external data of lithium-ion batteries such as battery capacity, as training samples, establish a simple model and input new data to get predicted values of RUL of lithium-ion batteries. And self-learning and repeated training and modification to obtain a final output. The neural network methods can estimate remaining service life of all kinds of batteries. In the applications of neural networks, there is no need to establish a separate mathematical model, nor to consider the chemical reaction of batteries. Only a good neural network model can be established based on appropriate samples to complete estimation. Meanwhile, with an increase of sample data, estimation accuracy will also be improved. Wu et al. [127] defined RUL by analyzing a terminal voltage curve of a battery at different cycles during charging. They proposed a feedforward neural network (FFNN) to simulate the relationship between RUL and charge curve and used importance sampling (IS) for FFNN input selection. Finally, an accurate estimate of RUL was obtained. Zhang et al. [128] used a LSTM recursive neural network (RNN) to learn the long-term dependence between degradation capability of lithium-ion batteries. RUL can be predicted earlier than traditional methods.

(2) Support vector machine (SVM) based methods

SVM was first proposed in 1995 and then applied to many systems. It is a method based on statistical theory, especially suitable for solving the remaining service life and small sample problems of nonlinear systems. It can also be generalized with the function fitting problem of machine learning. Its advantage lies in that it only needs less training data, and support vectors obtained by SVM training directly determines the amount of computation, which weakens a dimensionality problem to a certain extent, and it is also widely used in the prediction of lithium-ion battery degradation. Patil et al. [129] analyzed the cycle data of lithium-ion batteries under different operating conditions and extracted key features from voltage and temperature curves to construct classification and regression models for RUL. Classification models provided rough estimates, support vector regression (SVR) models to predict accurate RUL as a battery neared the EOL. Al-dulaimi et al. [130] took a rise of terminal voltage and a variation of voltage derivative (DV) in a battery charging process as training variables of a SVM algorithm to determine battery RUL. Then, SVM was used to establish a battery degradation model and predict actual cycles of a battery. Results showed that compared with a NN method, the proposed model has higher accuracy and less computation time.

(3) Gaussian process regression (GPR) based methods

GPR is a nonlinear regression probability method. Based on statistical learning theory and a Bayesian framework, Gaussian process regression gives the estimation of a posterior distribution by limiting a prior distribution of available training data and then obtains an uncertainty expression of prediction results suitable for the small sample and high-dimension regression problems. Moreover, it has the characteristics of self-adaptive and easy realization of hyperparameters. Jia et al. [131] constructed battery health indicators to represent battery capacity degradation from voltage, current, and temperature curves during charging and discharging. SOH prediction is carried out by combining a GPR method with probability prediction, and an input of prediction is obtained by grey correlation processing of some indexes. RUL is estimated by its mapping relationship with SOH.

(4) Filtering algorithms based methods

There are many random filtering algorithms [132], such as particle filter and Kalman filter particle filter methods in non-linear non-Gaussian predicted estimates often cited, its principle is based on the Bayesian theory according to known data to predict future, but its limit noise that must be Gaussian noise but will be able to make the uncertainty of prediction results express that predicted results of a probability distribution. Therefore, many scholars used this method to predict the life of a lithium-ion cell. KF algorithms are an autoregressive processing algorithm based on optimization. Its core is to minimize the state variance estimation of a system and calculate an estimated value of a state through the basic equation of a system. The advantage of this process is that it can use computers to calculate data in real-time. At the same time, this algorithm can be used for nonlinear systems with a wide range of applications. Qiu et al. [133] used a multi-scale hybrid Kalman filter (MHKF) consisting of a backward smoothing square root cubature Kalman filter (BS-SRCKF) and an EKF to jointly estimate SOC and SOH. An improved Cuckoo search (ICS) algorithm was combined with a standard PF. Finally, the RUL prediction was realized based on joint estimation information.

(5) Stochastic process based methods

Wiener process is also a common stochastic method in reliability modeling, which is suitable for a degradation process with Gaussian noise and a bidirectional change with time. It is also called a Brownian process. Using the Wiener process to model a degradation process has a certain mathematical solution advantage [134]. Using a Wiener process to model a failure time distribution can be analytically expressed, called the inverse Gaussian distribution. Wang et al. [135] proposed a prediction method based on multi-implicit nonlinear drift Brownian motion and applied it to prediction of rechargeable battery RUL. Wu et al. [136] proposed an online prediction method based on a gamma process model, established battery PDF and reliability curve, and obtained a confidence interval of 0.95 to reveal a predicted RUL statistical profile, taking into account uncertainties arising from random charge-discharge cycles.

(6) Other methods

Other data-driven methods are also briefly described here. Severson et al. [24] developed an RUL prediction model using early cyclic discharge voltage data generated from a battery under the condition of rapid charging which did not show capacity degradation and used a machine learning algorithm to accurately predict RUL. Ma et al. [137] proposed an algorithm based on a joint neural network and pseudo-nearest neighbor method and verified the effect of the algorithm by predicting RUL of batteries with different nominal capacities. Ng et al. [138] proposed a method for RUL prediction of lithium-ion batteries under different operating conditions based on a naive Bayes method and gave an uncertainty measurement of prediction results, which showed good robustness. The data-driven methods have stronger flexibility and applicability. It does not require professional knowledge of an internal reaction mechanism of a battery system but needs high-quality battery data as a basis for model training.

4.2.2 Model-Based Methods for RUL Prediction

Model-based methods usually construct a physical degradation model or experiential model to describe a battery under relevant characteristics, and then RUL can be obtained by extrapolation methods. The steps of the model-based methods can be summarized as the following. Firstly, according to the characteristics of historical data to select an appropriate model (such as electrochemical model, equivalent circuit model, or half-empirical model). Secondly, a selected model can be transformed into a state-space equation by a filtering algorithm (KF, PF, etc.). Thirdly, get initialized parameters and then estimate and update state variables by using historical data. Finally, extrapolating a measurement equation to get an updated model and predict RUL of Li-ion batteries. Qiu et al. [133] embedded an improved cuckoo search (ICS) algorithm into a standard PF to improve the performance of the algorithm. Zhou et al. [139] used a KF algorithm and fuzzy logic (FL) to estimate capacity and control observation noise with the help of cloud platform data of electric vehicles and established an Arrhenius empirical model to predict RUL of a battery pack. Downey et al. [140] realized online RUL prediction by using a nonlinear least squares method with dynamic bounds. Generally speaking, this method was a model established for a specific system. The model-based methods do not have generality and modeling process is complicated, requiring certain professional knowledge.

4.2.3 Fusion Methods for RUL Prediction

Fusion methods usually combine model-based and data-driven approaches. There have been many studies using fusion models to predict the RUL, Xing et al. [30] proposed a model combining an empirical exponent and polynomial regression and used a PF method to update model parameters and then obtain RUL prediction results with higher accuracy. Chang et al. [36] proposed a fusion method based on the idea of error correction, which combined a completely set empirical mode decomposition (CEEMD) algorithm and a relative vector machine (RVM) algorithm and could accurately predict RUL of batteries with different calibration capacities and discharge currents. Jiao et al. [141] proposed a battery RUL prediction algorithm based on conditional variational autoencoder (CVAE) and PF, which obtained a better RUL prediction effect and smaller prediction uncertainty than PF. Xue et al. [142] proposed an integration algorithm combining an adaptive unscented Kalman filter (AUKF) and support vector regression (GA-SVR) optimized by a genetic algorithm, which improved accuracy of RUL prediction. This method can integrate advantages of two methods and obtain a better prediction effect than a single model. However, the type selection of sub-models and the principle of model fusion need to be further studied. Li et al. [116] proposed a novel integrated method based on a mixture of Gaussian process (MGP) model and PF for SOH estimation of lithium-ion batteries under uncertain conditions.

For battery health status estimation and health management, more advanced approaches that fuse data-driven and model based methods are needed. Then, both SOH and RUL can be real-time and accurately obtained for battery health management.

4.3 Predictive Maintenance Methods

The above discussed topics are basics of maintenance, providing useful health information for maintenance. Generalized predictive maintenance concludes SOH and RUL prediction. The goals of device maintenance stand in decreasing costs and unnecessary servings under the premise of guaranteeing reliability and safety [143, 144]. Conventional maintenance methods tend to be passive and planned, lack automation and intellectualization. Existing scheduled maintenance and breakdown maintenance are typically much dependent on human decision-making, which causes poor efficiency and high costs.

In recent years, predictive maintenance, as known as condition based maintenance, has been gaining fresh prominence as optimal maintenance policy [145]. An objective function is to set as a maintenance cost so that to some extent, the predictive maintenance can be regarded as an optimization problem. Besides, the predictive maintenance allows operators to do scientific decision-making and give feedback on product designs. Many novel methods were presented to proceed with the predictive maintenance, especially ML based methods [146].

As for the battery PHM field, the predictive maintenance can be beneficial to ensuring battery designed life and prolonging life with a low investment [147]. Also, related literature is scarce because it is an emerging area that lacks knowledge. With the virtue of a proportional hazards model, Hu et al. [145] presented an RUL prediction approach and further derived optimal maintenance strategies to minimize a system cost. It was a comprehensive model, not only can predict RUL but also can provide a predictive maintenance policy. Reallocation and replacement of battery cells can be a way of predictive maintenance. Sun et al. [148] studied components that are in series systems and presented a maintenance policy to balance degradation degree between components in one system. This thought is potential in future battery applications.

There is still much space in the predictive maintenance. In battery industry, just elementary predictive maintenance strategies are considered, and accuracy in reality remains to be discussed [149]. The most studies only stay in theoretical shelf so more efforts should be made to apply a predictive maintenance policy to real experiences.

For predictive maintenance, there is a long way to go. Using advanced algorithms such as AI and uncertainty theory that help design predictive maintenance strategies are needed in the future research.

5 Challenges of Battery PHM and Future Research Opportunities

This section discusses some challenges and opportunities of battery PHM from various aspects.

5.1 Challenges and Problems for Battery PHM

Although there has been a lot of preliminary progresses in the research on battery PHM, there are still many challenges and problems.

Some main challenges are summarized as follows:

(1) System-level prognosis is needed. There are few SOH and RUL prediction methods for battery packs, most methods only focus on battery cells. System degradation and health status of batteries are rather crucial for electric devices. Healthy states of various battery cells in battery pack are different because of battery inconsistency. System-level prognosis should consider the inconsistency while modeling. Besides, health states of battery pack are synergistic effects combining all cells, this will bring difficulties for prognosis.

(2) To promote practical applications of battery PHM, more research based on onboard data is necessary. Most studies are based on laboratory datasets of ALT, which may not fit complicated real scenarios. The reality is more complicated and changeable, and laboratory conditions cannot meet all these environments. The adaptability of algorithms based on laboratory data in real situations is a test. Thus, multiscale data should be collected for model development and algorithm verification. More real data should be collected and used for modeling.

(3) Prediction uncertainty is difficult to quantize. Because of sensor inaccuracy, lacking of systematic knowledge, and diverse environment, sources of uncertainty are wide, containing model uncertainty, measurement uncertainty, environmental uncertainty, etc. Many factors such as season, temperature, road condition, user behavior, may influence results. Thus, future methods should thoroughly consider different sources of uncertainty based on uncertainty theory.

(4) The robustness of existing methods is not strong, which is difficult to deal with battery PHM under extreme environments and unknown loadings. More general and strong methods are needed.

(5) Health management related research is insufficient. Health management requires multi-faceted coordination, including manufacturers, users, maintenance service providers, etc. It is difficult to realize information collection and cooperation. According to the survey, seldom predictive maintenance policies have been proposed, there still remains some research gaps. More theories such fuzzy theory will be explored to help realize battery health management.

5.2 Prospect of Future Research Opportunities for Battery PHM

With the rapid development of AI and cloud computing, higher requirements will be put forward in battery PHM. Meanwhile, development opportunities are provided in future research.

Future research opportunities are given as follows.

(1) With the virtue of big data cloud platform, online and remote battery PHM might be possible. Combining battery PHM with Internet of Things (IoT), networked and intelligent battery PHM systems will come true.

(2) Hybrid prognosis methods and physical-informed data-driven methods will play a vital role in battery PHM in the future because of their high robustness and universality.

(3) Novel nondestructive inspection technology and advanced high-precision sensors are of increasing and urgent demands for battery PHM.

(4) Digital twin technology applied for battery PHM is worth exploring. Battery digital modeling will make battery PHM more accurate and reliable. It can further promote realizing the digital management of equipment life cycle, reduce operation and maintenance costs, etc.

(5) Development of edge computing will provide the computational ability and historical data required by data-driven battery PHM algorithm.

(6) Transform learning, such as domain adaptation, enables the algorithm to serve a variety of models and batteries.

6 Conclusions

With the help of new technologies such as AI, battery PHM has good foreground in the future. This paper systematically reviewed battery PHM from the perspective of main PHM steps. Extensive publications were analyzed to review a recent development of battery PHM in recent six years from 2018 to 2023.

The main findings are summarized as follows.

(1) Firstly, battery testing and public datasets were vital as a foundation of battery PHM. Various kinds of battery testing were summarized, including general electrical performance testing, life cycle testing, safety and reliability testing. Public datasets from academic and industrial institutions led by NASA ProE were collected. Characteristics and features of each dataset were analyzed in order to provide convenience for researchers. Although there were lots of experimental public datasets, more on-board battery datasets were of demand.

(2) Secondly, we reviewed battery diagnosis and prediction methods. Battery faults can be divided into three categories: External battery faults, internal battery faults and thermal runaway. Battery diagnosis and prediction methods can be classified into two types: Model and experiment based methods and data-driven methods. More powerful and reliable diagnosis and prediction methods should be explored to minimize security risks.

(3) Thirdly, SOH estimation methods and RUL prediction methods were discussed. Generally, they contained data-driven methods, model based methods and hybrid methods. Data-driven methods developed fast due to the coming of big data era, so we primarily focused on them in this paper. Predictive maintenance

methods are under a development and will be a trend in the near future. The coming battery PHM will be more intelligent, automatic and self-adapting. Combining new technologies like AI, IoT, cloud computing, battery PHM will go up to a new level.

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Authors' Contributions
JK and DW conceived this paper; JK was in charge of the whole trial; JK, JL, JZ and DW wrote the manuscript; DW, ZP, KT and XZ supervised the study and provided funding support. All authors read and approved the final manuscript.

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Data Availability
Data are not available.

Declarations

Competing Interests
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