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Review Article

Remaining life prediction of lithium-ion batteries based on health management: A review

Kai Song [a,b,*], Die Hu [a], Yao Tong [c,**], Xiaoguang Yue [d]

[a] School of Life Science, Changchun Normal University, Changchun, China
[b] Institute of Science, Technology and Innovation, Changchun Normal University, China
[c] Hoffmann Institute of Advanced Materials, Shenzhen Polytechnic, Shenzhen, Guangdong, 518055, China
[d] Department of Computer Science and Engineering, School of Sciences, European University Cyprus, Nicosia 1516, Cyprus

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ABSTRACT

Lithium-ion battery remaining useful life (RUL) is an essential technology for battery management, safety assurance and predictive maintenance, which has attracted the attention of scientists worldwide and has developed into one of the hot issues in battery systems failure prediction and health management technology research. This paper focuses on developing a Lithium-ion battery remaining practical life prediction algorithm to improve its adaptability and accuracy. To achieve this goal, the fusion model methods based on data-driven, model-driven and the combination of the two are summarized, and the problems they face are discussed. Accurate estimation of the remaining life of lithium batteries not only allows users to obtain battery life information in time, replace batteries that are about to fail, and ensure the safe and efficient operation of the battery pack but also ensures that lithium-ion batteries are used as the primary energy supply and energy storage to a large extent. The safety and reliability of the equipment in its operation avoid accidents and reduce operating costs. It focuses on the methods and research status of lithium-ion battery remaining life prediction at home and abroad and the main factors affecting battery life and prediction accuracy. In this paper, the advantages and limitations of various prediction methods are summarized and compared, the current technical research difficulties are outlined, the urgent problems to be solved, and the development trend of battery life prediction technology research are given.

1. Introduction

Lithium batteries can be used as energy supply units, replace old lead storage batteries, and have become popular goods in the battery business due to their high specific energy, long life, and lack of memory. Lithium-ion batteries provide undeniable convenience in a variety of applications. However, it still exhibits potential safety hazards. For example, the Samsung note7 battery explosion, China Southern Airlines flight CZ3539 passenger lithium battery mobile power supply caught fire, Tesla repeatedly caught fire, Build Your Dreams (BYD, a car company) SUV hybrid vehicle spontaneous combustion incident. Lithium-ion batteries' ageing and performance decline are one of the causes of these lithium-ion battery safety events. In general, the performance of lithium-ion batteries degrades over time when they are charged and discharged. As a complex system with random electrochemical changes, the internal state parameters of lithium-ion batteries cannot be measured by sensors.

Furthermore, employing physical probe methods to detect the health condition of lithium-ion batteries in practical applications is problematic. As a result, the battery capacity (for example, energy storage capacity) can be utilized as a scale for State of Health (SOH) prediction using readily available variables such as current, voltage, and temperature. Through lithium-ion battery ageing experiments, it can be determined that the film-forming reaction of the negative electrode Solid-electrolyte Interphase (SEI) of the lithium-ion battery and the degradation of the positive electrode active material are the main reasons for the battery performance failure and the use under high temperature or low-temperature environment is also a significant cause of performance failure [1–4]. For example, carbonaceous materials are modern lithium-ion batteries' most common anode materials. The SEI

* Correspondence to: K. Song, School of Life Science, Changchun Normal University, Changchun, China.
** Corresponding author.
E-mail addresses: songkai@ccsfu.edu.cn (K. Song), yao_tong@szpt.edu.cn (Y. Tong).

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layer formed on the carbon surface during the cycle will cause irreversible capacity loss [5–8]. The irreversible process leads to continuous capacity degradation and, eventually, battery failure. Especially in astronaut wearable devices, if the lithium battery reaches the failure threshold and safety measures such as replacement or maintenance are not taken in time, it may cause serious consequences. Therefore, lithium-ion battery capacity deterioration and RUL prediction research have risen in importance. It has become a research hotspot owing to the high safety and reliability of lithium-ion batteries in aerospace.

To effectively manage so many batteries in the car battery pack, protect the battery and the battery pack from being damaged, make the battery work in the appropriate voltage and temperature range and prolong its service life as much as possible to meet the needs of the vehicle, Battery Management System (BMS) is essential. The framework of a standard battery management system is shown in Fig. 1, which is mainly composed of software and hardware. BMS can achieve reasonable control and management of battery operation by monitoring data acquisition of lithium-ion batteries, cycle charge and discharge management and temperature monitoring to reduce battery failures [9,10]. BMS mainly includes battery balance management, overvoltage and overcurrent protection, temperature control, data collection and storage, battery state estimation and prediction, etc. [11,12].

The battery State estimation and prediction mainly include two parts: one is the state of health (SOH) of the lithium-ion battery, and the other is the Remaining Life (RUL) prediction. SOH is used to characterize the overall degradation of battery performance, and the degradation degree can be seen through the S0H estimation of lithium-ion batteries [13]. RUL is an index used to evaluate the battery's health status, which refers to the charging and discharging times of the lithium-ion battery when it reaches the capacity failure threshold under specific charging and discharging conditions from the current moment [14]. Therefore, an accurate RUL prediction of lithium-ion batteries can provide beneficial information when replacing and repairing power systems, reducing the economic and human cost of lithium-ion battery failures. State estimation and life prediction of lithium-ion batteries are critical technologies in the BMS system, which can provide practical information for system management and have essential research significance and value [15].

Accurate prediction of the RUL of lithium-ion batteries has become more significant in evaluating lithium-ion batteries' status and health management in recent years [16]. As science and technology have progressed, deep learning approaches have become widely used in various industries. Machine learning is where the concept of deep learning comes from [17]. It performs feature learning on data and can automatically acquire features. There is no need to use the manual acquisition of features. It's structure is inspired by the biological nervous system and the continuous development of computer hardware [18]. The efficiency of deep learning methods is gradually increasing. Artificial intelligence (AI) and deep learning have become more efficient in recent years. Continuous progress has led to new data-driven methods for the above problems. Deep Neural Networks (DNNs) [19], notably Convolutional Neural Networks (CNNs) [20] and Recurrent Neural Networks (RNNs) [21], are ideal for training multi-layer artificial neural networks for high-complexity linear fitting. Higher accuracy can be attained for complicated prediction problems like multi-battery RUL estimation, boosting the battery system's safety and usefulness while giving battery system managers and users beneficial suggestions.

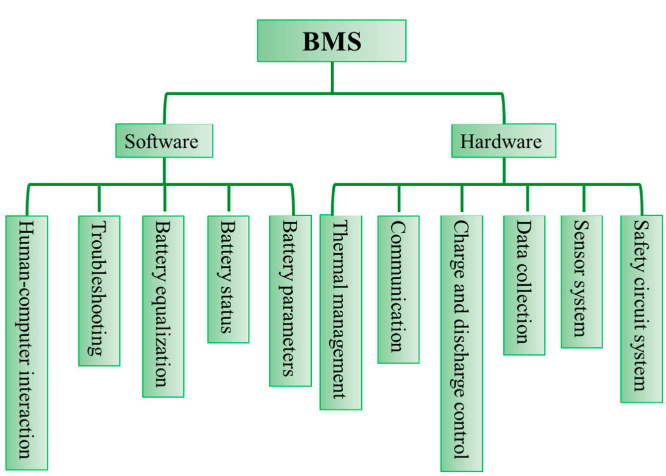

Fig. 1. Basic framework of battery management system.

Meanwhile, with the continuous industry development, more and more data are generated in various production and experimental processes. These data can suit the needs of deep learning approaches that demand enormous amounts of data. The disadvantage of deep learning is that it necessitates a considerable amount of data for the model to be trained. As a result, using deep learning approaches to forecast the URL of lithium batteries has become the most popular approach [22–24]. Among many methods, the most frequent is the public lithium battery data set of the NASA PCoE Experimental Center [25]. This data set includes many parameters of the battery charging and discharging processes, which provide much information for battery life prediction. Therefore, using this data set to study lithium-ion battery life prediction methods can generate more valuable information in this field.

In summary, with the increasing requirements for battery safety in related fields, the ability to accurately and quickly predict the life of lithium batteries improves the safety of related fields. It saves them a lot of money and time. As a result, a method that can adequately forecast the RUL of lithium-ion batteries is essential for practical use. Compared with other works [26], the present manuscript systematically sieves a machine learning-based RUL prediction method for lithium-ion batteries. Through a comprehensive and cutting-edge review, constructive development suggestions for machine learning in Li-ion battery RUL prediction are put forward. This work collects lithium-ion battery RUL prediction approaches based on data-driven, model-driven, and fusion models to enhance the accuracy of lithium-ion battery RUL prediction. Comparing their development and the advantages/disadvantages provides a reference for researchers to choose a suitable lithium-ion battery RUL prediction method in various situations.

2. Definition of Li-ion battery status

The battery's SOH must be established to forecast the battery's RUL. Battery RUL is usually forecasted by identifying the SOH of the battery. The RUL prediction model's significant predictive property will be SOH. As a result, understanding the concept of SOH is crucial. The battery's SOH is described as the ratio of the present state's actual capacity to the initial state's rated capacity [27], as shown in formula (1):

$$\mathrm{SOH} = \frac{C_{act}}{C_{norm}} \times 100\% \tag{1}$$

Among them, C_{act} and C_{norm} represent actual capacity and rated capacity respectively. SOH can be used to describe the state of a battery's ageing and degradation. Generally, when the battery capacity is reduced to 70 % ~ 80 % of the rated capacity [28], the battery is regarded to be in a failure state and cannot be used continuously, indicating that the battery should be replaced as soon as possible. Another characteristic that indicates a battery system's reliability is its State Of Charge (SOC), which may be represented as the ratio between the available charge and the maximum charge [29], as shown in formula (2):

$$\mathrm{SOC} = \frac{Q_C}{Q_N} \times 100\% \tag{2}$$

where Q_C denotes the battery's available charge capacity, and Q_N denotes the battery's maximum charge capacity. SOC and battery capacity do not have a strong relationship. The degraded battery capacity over time is the key indicator for long-term prediction of the battery. Therefore, SOH is a better choice for the RUL prediction attribute than SOC. The battery's RUL can be anticipated further using the expected SOH.

The RUL of a Li-ion battery is the amount of time (charge and discharge cycles or the number of cycles) between now and the End of Life (EOL) [30]. Fig. 3 depicts the basic concept of Li-ion battery RUL. The charge and discharge cycle (number of charges and discharge cycles) is represented on the horizontal axis, and the unit is cycling (cycle). In contrast, the battery capacity is represented on the vertical axis, and the unit is Ampere hour (Ah). The rated capacity of a lithium-ion battery refers to its initial capacity. The absolute capacity of the lithium-ion battery would eventually diminish due to repeated charging and draining during operation. When a lithium-ion battery's actual capacity degrades to 70 % (or 80 %) of its rated capacity, it is said to have reached the failure threshold, and the charge and discharge cycles (cycles) between the current moment and the actual capacity reaches the failure threshold are the battery's RUL. RUL prediction of lithium-ion batteries refers to using previous capacity degradation data prior to the current period to learn the capacity degradation trend model. The learnt model is utilized from the current period to gradually extrapolate future capacity until the estimated battery capacity hits the failure threshold. The charge and discharge cycles (number of cycles) experienced by this capacity extrapolation process are the predicted RUL.

The capacity degradation curve in Fig. 2 is relatively smooth and monotonously decreasing, which is an ideal degradation process. The actual capacity degradation process is much more complicated. This is because the battery's capacity will rise after being left for some time, and it is not monotonously decreasing. Moreover, the capacity degradation in the early stage is slow, and the degradation gradually accelerates in the later stage. Generally, it is a nonlinear and fluctuating degradation process. This makes RUL predictions more difficult. Moreover, the larger the capacity and the longer the charge and discharge cycle, the more difficult it is to predict RUL.

3. Current status of research on methods for predicting the RUL of lithium-ion batteries

To ensure the lithium-ion battery system's reliable operation, a process must be in place to assess the lithium-ion battery system's State of Health (SOH) and estimate the RUL, which can assist manufacturers in determining when to remove or replace lithium-ion battery reference information. Prognostics and Health Management is the system's name for assessing the health of lithium-ion batteries (PHM). Condition-Based Maintenance (CBM) is a vital function of the lithium-ion battery PHM system [32,33]. CBM is a preventive method, meaning maintenance is only performed when essential. To assess whether or not to do CBM, it is usually possible to continuously evaluate the battery's health [34]. CBM includes two main tasks: diagnosis and prediction. Diagnosis is the process of identifying battery failures and current health conditions, which can be described as estimating the SOH of the battery. At the same time, prediction is estimating how much time is left before the battery failure occurs and can be described as predicting the RUL of the battery. CBM must be integrated with the functioning of the battery system to avoid significant negative repercussions when the battery system fails, and precise battery failure prediction is the key to CBM.

The failure prediction of the battery system involves two stages. The first stage seeks to assess the battery's present SOH, while the second stage aims to calculate the RUL by forecasting the SOH's degradation trend. Therefore, RUL prediction is critical in the battery PHM system [35]. Fig. 3 shows the general layout of the battery PHM system. The steps are often classified into the following categories:

1) Collect raw battery data, such as current, voltage, impedance, and capacity.

2) Data preprocessing, such as normalization, to extract the characteristic data.

3) Development of Health Indicators (HI). To create HI, the characteristic data is processed. The battery capacity is the most commonly used HI and is used to characterize the battery's SOH.

4) RUL prediction based on SOH estimation to predict the length of time before the battery life expires provides CBM with decision support.

5) To address the problem of uncertainty, the RUL point estimate prediction is converted to an interval estimation forecast, allowing the RUL forecast result to convey uncertainty.

RUL prediction is the final premise for providing decision support for CBM in the lithium-ion battery PHM task in Fig. 2, and precise RUL prediction is the main task of the battery PHM architecture. Since lithium-ion batteries of different chemistries follow different degradation paths, there is much information about the failure modes of lithium-ion batteries. Even batteries with the same chemical properties designed by different manufacturers generally cannot provide the same performance. The degradation process of every single cell is different, and its corresponding mechanism degradation model is also different. Although the lithium battery RUL prediction method based on the mechanism degradation model has high prediction accuracy, an accurate mechanism degradation model is often challenging to obtain. However, there are many data-driven RUL prediction methods for lithium batteries, and there is no absolute best model and unified general model. When using a single data-driven RUL prediction approach for lithium batteries, the prediction performance is frequently limited; however, combining numerous data-driven RUL prediction methods can significantly enhance prediction performance.

The remaining service life forecast of the battery is an integral part of the research content for life prediction and health management of lithium-ion batteries. It is difficult to precisely anticipate the remaining

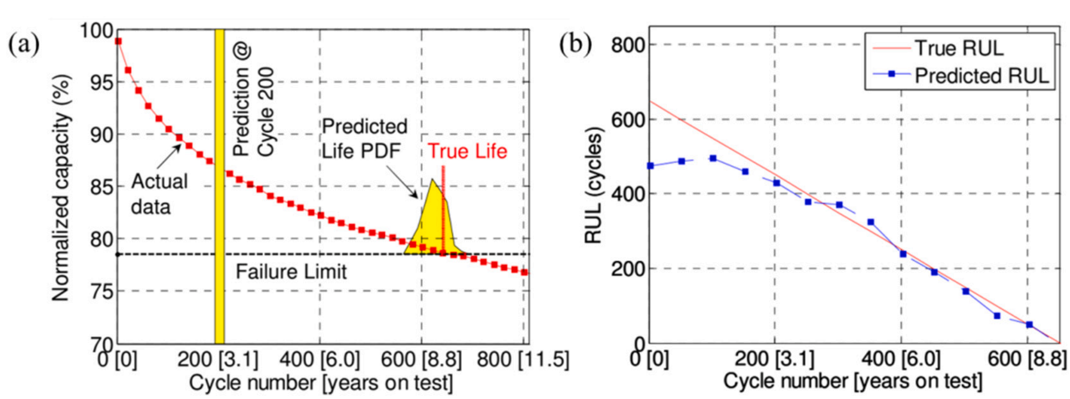

Fig. 2. The basic idea of battery RUL prediction: (a) Capacity tracking and RUL prediction in the 200th cycle; (b) RUL prediction in multiple cycles Cycle through the entire life cycle [31].

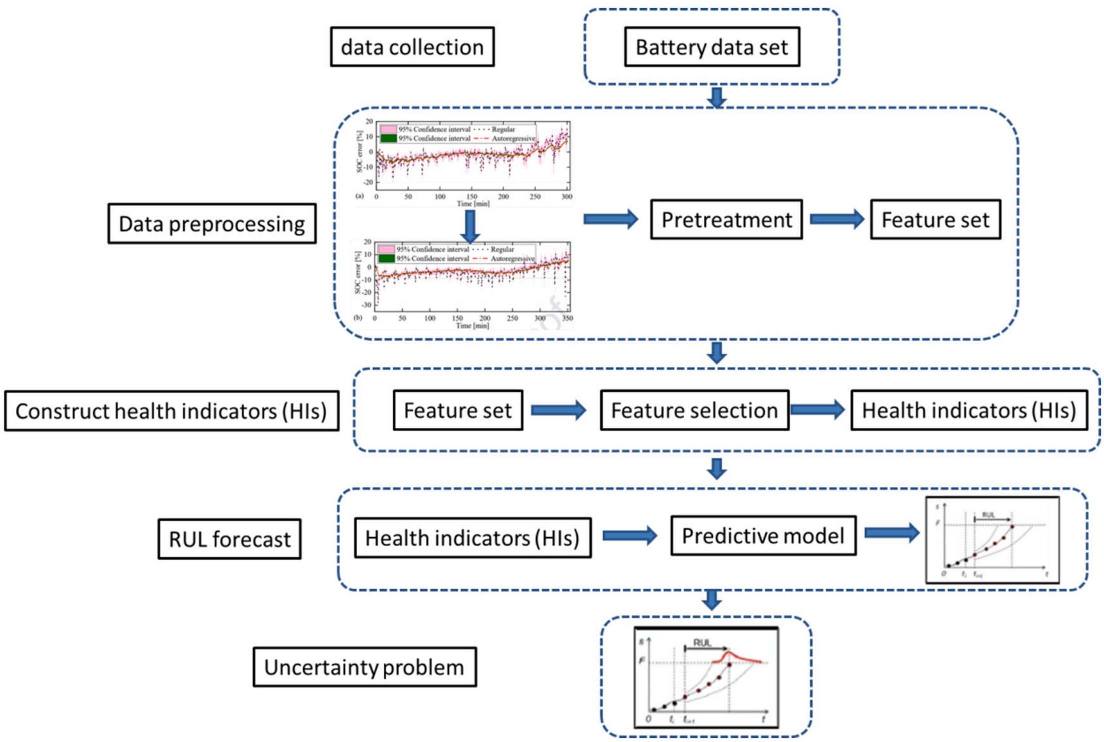

Fig. 3. Schematic diagram of the overall framework of a lithium-ion battery PHM.

life of a lithium battery using the characteristics obtained by measuring the battery during the charging and discharging process. Predicting the RUL of a battery can be done in a variety of ways. For example, Goebel et al. [36] proposed a series of data-driven and physical-based battery RUL prediction methods from probabilistic regression models to particle filters. However, due to the unavailability of data and the complexity of the battery model, there is currently no so-called best general model for predicting battery RUL. Three types of RUL prediction algorithms can be divided into three categories. The RUL prediction approach is based on the predicted object's physics, chemistry, or experience. However, the data-driven approach does not require formulating a specific system mechanism model based on past feature data. The third is the fusion method, in which multiple RUL prediction methods are fused differently. The different RUL prediction methods are summarized as shown in Fig. 4.

In addition, the above three types of methods can be divided into offline and online situations. Offline models are typically utilized when there is a significant volume of historical data and there are few real-time requirements. Offline models can fully train a significant amount of historical data while also enhancing the model's accuracy. Using a considerable amount of historical data for offline learning is not appropriate. It usually uses online models to learn from real-time data for times with more real-time requirements.

3.1. Prediction method driven by model

The model-based approach focuses on identifying and analyzing the main ageing mechanisms of lithium-ion batteries. By establishing an appropriate model based on the relationship between the battery's state of health and model parameters, the battery's state of health is estimated [37]. Commonly used models can be divided into two categories: mechanism models and equivalent circuit models. The method based on the mechanism model needs to study the influence of ageing factors such as external state, state of charge, electrolyte concentration, and diffusion coefficient on state variables. At the same time, the battery's internal operating mechanism and ageing mechanism must also be considered. The parameters of the battery mechanism model are generally obtained according to the physical characteristics of the electrode material. After the parameters are determined, the battery response and ageing problems under a given operating environment and charging and discharging conditions can be calculated. To estimate its RUL, the mechanism model-driven prediction technique uses knowledge of the battery life cycle load circumstances, geometry, material attributes, and failure mechanism [38,39]. This method has been studied for years, and the overall system is relatively mature.

The mechanism-based method identifies the correspondence between observables and indicators of interest by establishing a physical model of the degradation process that affects battery life. For example, Santhanagopalan and White used a strict high-rate-limiting porous electrode model and an odourless filter [41]. The empirical exponential growth model of lithium-ion battery resistance degradation was studied by An et al. [42], who used standard Particle Filter (PF) and resampling techniques to evaluate degradation data displaying the system's health at different time intervals, as shown in Fig. 5. Su [43] et al. used two empirical index models to predict and used PF to optimize the relevant parameters of the model and got good results. To characterize the open circuit voltage, current, temperature, and other dynamic characteristics of the battery, Dalal et al. [44] suggested a PF-based lumped parameter battery model. Hu et al. [31] adopted a simplified equivalent circuit model and applied Gauss-Hermite Particle Filter (GHPF) technology to track the capacity attenuation trend and predict the future capacity value. This is an extension of the particle filter PF technology. Li et al. [45] also use GHPF technology to estimate the battery state of charge, enhancing estimation accuracy while reducing the number of sampled particles and the algorithm's complexity. Li et al. [46] developed a universal capacity model based on fitting charging curves to forecast the SOH of Li-ion batteries. Miao et al. [47] created a degradation model in accordance with the Unified Particle Filter (UPF) to forecast the RUL of Li-ion batteries. The suggested model predicts RUL more accurately than the PF technique, with an error of less than 5 %. To assess the RUL of 26 lithium-ion batteries, Wang et al. [48] created a state space model based on the Spherical Cubature Particle Filter (SCPF). In terms of prediction

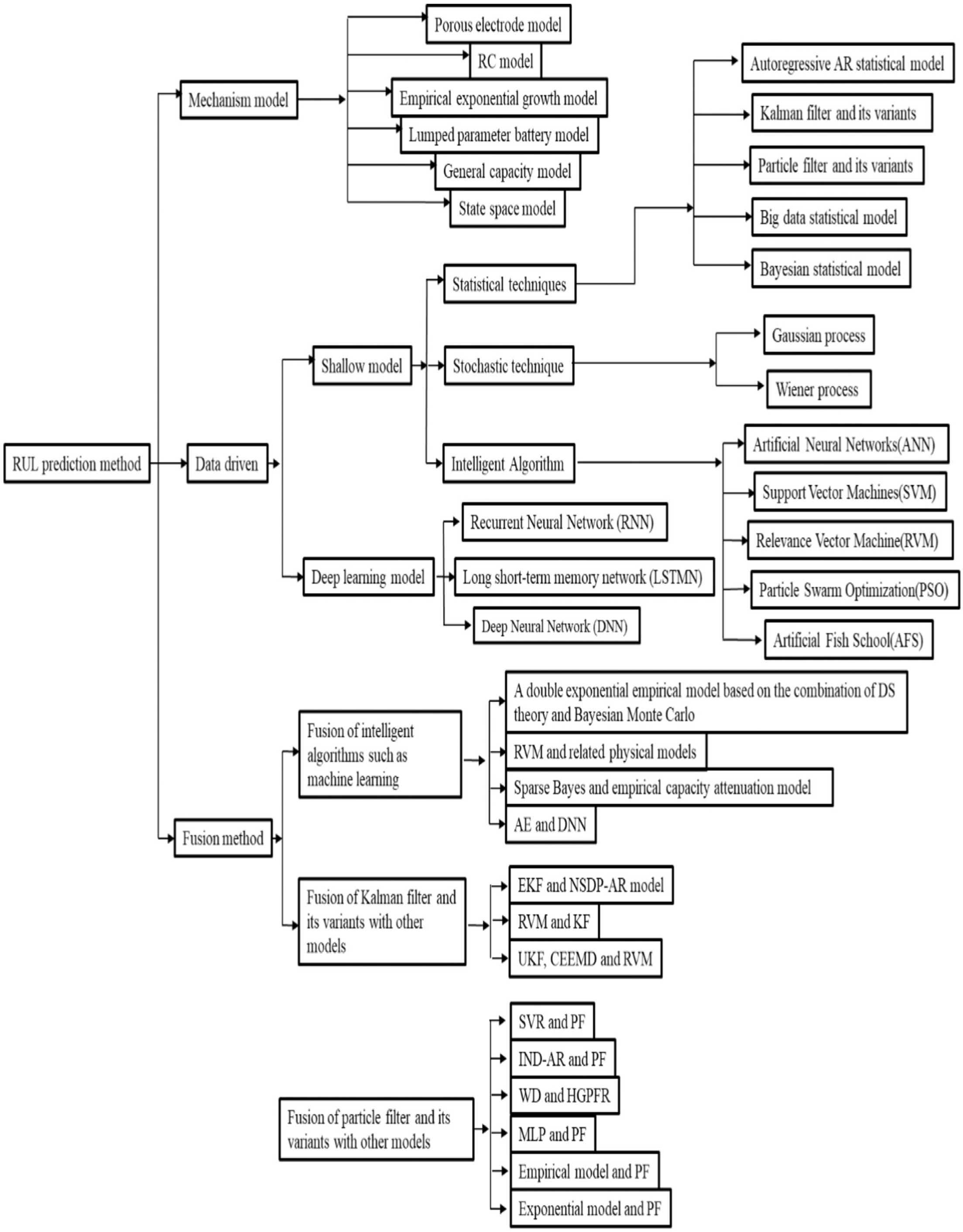

Fig. 4. The RUL prediction method for lithium-ion batteries.

accuracy, the suggested model outperforms the PF technique. Under generally stable external conditions, the RUL, as mentioned above, prediction approach in the light of the machine model can increase prediction accuracy. However, changeable current and temperature easily influence the model's performance. Furthermore, obtaining an accurate mechanism model under the effect of many external variables is difficult.

It is necessary to calculate and evaluate the prediction results by analyzing the mechanism of lithium battery life based on existing mathematical models to use the load conditions, material properties, geometry, and failure mechanism of the battery life cycle to assess its remaining service life (RUL). The electrochemical model is based on the electrochemical reaction inside a lithium-ion battery and is a tool for evaluating the law of battery performance decline. Rodrigues et al. [49] employed alternating current and impedance measurements to estimate the battery's remaining life. Piller et al. [50] compiled a list of commonly used SOC prediction algorithms and built a link between them and their applications. Lee et al. [51] examined the relationships between OCV and SOC in Li-ion batteries and used a dual-extended Kalman filter to forecast SOC and capacity. Salkind et al. [52] devised a feasible approach for predicting battery SOC and SOH that involves analyzing impedance spectroscopy and coulomb counting data with fuzzy logic. Singh et al. [53] created a fuzzy logic-based SOH meter for lithium-ion batteries, with EIS measurement as the input to the fuzzy logic (Fuzzy

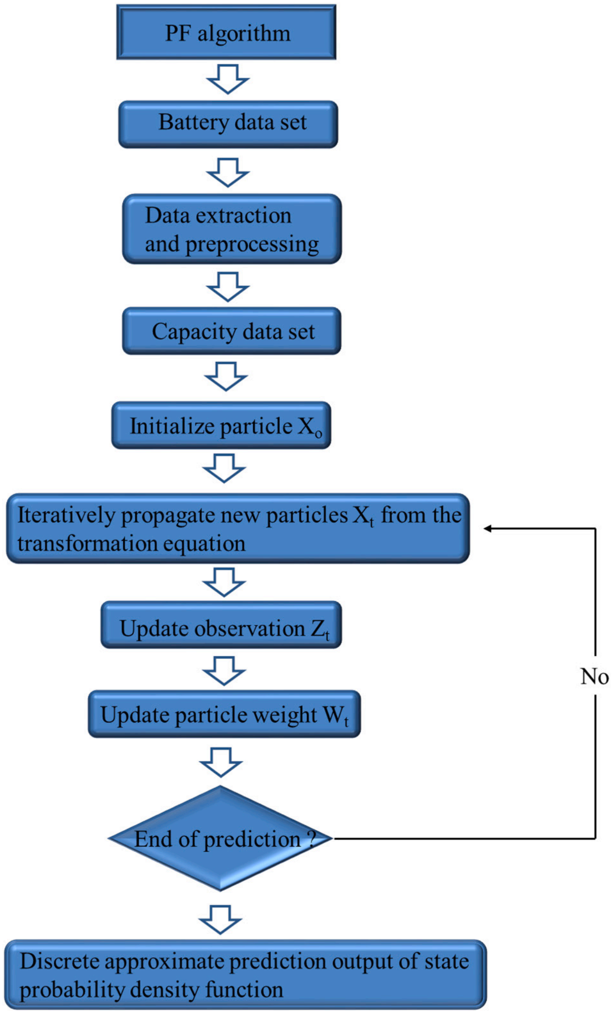

Fig. 5. Basic PF state estimation method [40].

Logic) model. Tsang and Chan [54] utilized fuzzy logic inference to build a battery SOH determination system based on lithium-ion batteries' detected equivalent Direct Current (DC) resistance in various health phases and operating temperatures. Even though the electrochemical model has a clear physical meaning, it has a high prediction accuracy and good interpretability. However, the model has many equations, and the calculation is tricky. The process of declining battery capacity is closely related to the operating environment and conditions. An electrochemical model cannot analyze all side reactions. The established model is not universal and has not been widely used in engineering.

Another way is to utilize an equivalent circuit model, an alternative to using circuit components to create a circuit with the same internal phenomena as a genuine battery to replicate the battery's charging and discharging operation. Because capacity will gradually decline with various age-related and degradation events, Miao et al. [47] used an exponential growth model to match the capacity degradation curve of lithium-ion batteries. Based on lithium-ion battery statistics, He et al. [55] used the sum of two analytic functions of the discharge cycle to simulate battery capacity loss. When defining the RUL of lithium-ion batteries in this fashion, they realized that resistance could be utilized as a health indicator. Eddahech et al. [56] used a single parameter from the EIS test to determine the battery RUL, which refers to the fundamental part of the impedance at a particular frequency. Kim's work [57] established a battery RC model in which capacity decay and resistance degradation were obtained from battery characteristic statistics and used to indicate battery health—defining RUL based on one or two battery parameter values, on the other hand, maybe insufficiently robust and inaccurate. When examining battery performance characteristics, Sun et al. [58] analyzed six contributing parameters to characterize the RUL in the references, analyzing their differences and expert opinions to solve this problem. Xing et al. [59] proposed a model incorporating an empirical index and polynomial regression model to monitor the deterioration trend of the battery during its cycle life based on the analysis of experimental data. He et al. [60] used multiple battery SOC to characterize the ageing condition of the battery since batteries with different ageing states will have different SOC-OCV (Open Circuit Voltage) curves.

In real applications, however, obtaining an accurate OCV is problematic. As a result, an acceptable definition of battery RUL is required for proper operation. On the other hand, many model-based solutions rely on closed-loop format filtering algorithms, in which the difference between model prediction and measurement is relayed back to rectify the state. Plett [61] proposed and demonstrated the use of an Extended Kalman Filter (EKF) for evaluating battery state and quantitative SOC estimates. Zou et al. [62] used two instances of EKF with different time scales for a combined estimate of SOC and SOH in a similar double-filtering architecture. Xiong et al. [63] presented and demonstrated the effectiveness of an adaptive EKF technique for battery status estimation. Xu et al. [64] computed the RUL of lithium-ion batteries that used a state space model. The model's parameters and states were modified using the Expectation Maximization (EM), and EKF approaches. By establishing a GENERAL state space model, the discharge profile of each period is approximated by the observation model, the corresponding parameter vector is regarded as the hidden state, and the state transition model tracks the evolution of the parameter vector with the battery life. As shown in Fig. 6, the modified model has a specific effect on tracking the degradation of actual battery performance. Hu et al. [65] proposed a Moving Horizon Estimation (MHE) for health monitoring in advanced battery systems using simplified electrochemical models. Although accurate for weakly nonlinear models, EKF necessitates costly Jacobian calculations and frequently fails when nonlinearity is significant. Some of the limitations of EKF [66] can be overcome with the Sigma-Point Kalman Filter (SPKF) (also called unscented Kalman filter). For the battery estimation algorithm, several authors applied SPKF. Plett [67], for instance, uses SPKF to calculate the SOC of lithium polymer batteries. For battery SOC and internal state predictions, Andre et al. [68] presented a double filter that combines KF and SPKF. They calculated the battery's SOH using the expected capacity.

Saha et al. [40] applied particle filters to estimate the coefficients of the exponential growth model of electrolyte resistance and charge transfer resistance. The relationship between electrolyte resistance, charge transfer resistance and capacity is established to infer future capacity from the predicted electrolyte resistance and charge transfer resistance. Finally, the RUL is calculated as the interval between the current cycle and the end of life (represented by the preset capacity value) cycle. However, the dependence on impedance measurement hinders the use of this prediction method in practical applications, which is mainly due to equipment costs, strict measurement requirements and space constraints. Saha and Goebel [69] constructed an empirical computing power model that addresses the Coulomb efficiency factor and relaxation effects without the usage of EIS equipment. The particle filter is used to extrapolate future capacity values for RUL estimates and to estimate the value of battery model components. Compared with previous papers, EIS measurements cannot infer internal battery parameters. Instead, a combination of empirical models was explored to represent the energy loss caused by IR drop, activation polarization, and concentration polarization. Dalal et al. [44] established a particle filtering framework for estimating the life of lithium-ion batteries, which makes use of a lumped parameter battery model to describe all of the battery's dynamic features. Kozlowski [70] built a two-electrode electrochemical model of the battery and verified it using

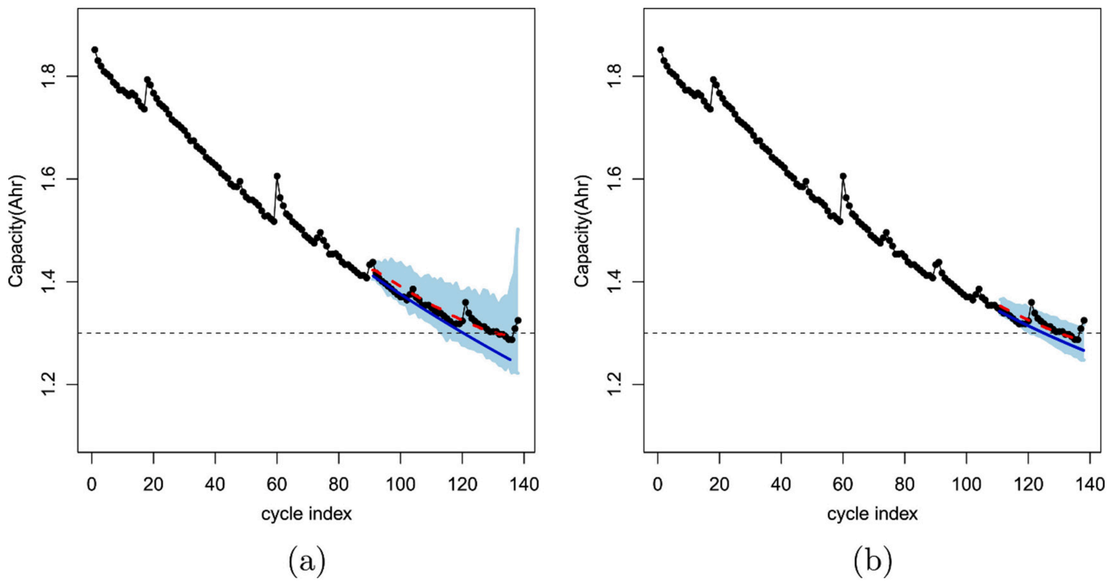

Fig. 6. Comparison of the capacity predicted by the two models based on data from the first 90 (a) and 110 (b) cycles, respectively [64].

measured impedance data. Gao et al. [71] established an empirical lithium-ion battery model that can estimate the OCV at a certain discharge rate and ambient temperature. Hirsch et al. [72] established a generalized normalized discharge voltage curve for lead-acid batteries. The comparison of the normalized measurement value with the general normalized discharge voltage curve will result in the determination of the discharge level and the percentage of reserve time (comparable to the total capacity required). Burgess provided a method for estimating the RUL capacity degradation trend of valve-regulated lead-acid batteries according to capacity measurement and Kalman filtering [73]. The decline is divided into two stages. There was a slow decline at first, followed by a sharp drop. The Kalman filter is engaged when the battery capacity reaches the second stage, and the probability capacity decay model is utilized to estimate RUL. However, because the second stage of battery capacity drop lasts a rather short time compared to the entire battery pack, that method cannot be used to predict battery life in the early phases.

Through the research on the model-driven method, it can be seen that although the model-driven method is effective in predicting the remaining life of lithium-ion batteries in some studies, it has some problems, as shown in Table 1. First of all, the model-driven method needs to establish an accurate model of the battery, which often takes a lot of time and requires very experienced experts to complete. Even if the construction of the battery model is completed, once the working environment of the battery is disturbed, the stability of the model will be affected, and the generalization performance of the model-driven method is generally poor. Moreover, many methods are more complex, which require a lot of professional knowledge and relevant experience. These reasons lead to the application of the model-driven method is not very extensive.

The equivalent circuit model uses traditional circuit components: resistors, capacitors, and controllable voltage sources to build circuit models. Currently, the commonly used models include Rint model, Thevenin model, PNGV model, and n-order RC model. Several typical equivalent circuit model structures are shown in Fig. 7.

Zhang et al. [75] proposed an equivalent circuit model parameter identification method considering electrochemical performance. And according to the relationship between the electrochemical parameters and the solid phase and electrolyte phase, the parameters of the equivalent circuit model are calculated. Combining the electrochemical transfer function and the equivalent circuit, the relationship between resistance, capacitance and electrochemical parameters is established.

Table 1
Comparison of common model-driven RUL prediction methods.

Method		Advantage	Disadvantage
Electrochemistry Model	Analytical solution	• Clear	• Large amount of calculation
	Numerical Methods	• Simplify the process	• Complicated calculation, not universal
Equivalent Circuit Model	Time domain analysis	• Intuitive and accurate	• Large amount of calculation
	Frequency domain analysis	• No need to obtain the output time-domain expression; • The stability and transient performance of the system can be studied; • Easily analyzed system performance; • The linear system and the nonlinear system can be analyzed.	• Not intuitive enough; • Not easy to understand; • Not able to reflect the moment of occurrence

Zou et al. [62] proposed a model-based SOC and SOH combined estimation method for ternary lithium-ion batteries. First, determine the SOC dependence of the nominal parameters of the first-order RC model, and quantify the performance degradation of the nominal model over the entire battery life. Secondly, two extended Kalman filter algorithms with different time scales are applied to realize the combined SOC and SOH estimation, one observer is used for real-time SOC estimation, and the other is used for offline SOH (capacity and internal resistance) update. Similarly, methods such as particle filter and sigma point Kalman filter have also been introduced into SOH estimation [67,76]. To better study the battery ageing process, some researchers have also proposed an improved equivalent circuit model, which separates the positive and negative electrodes of the battery, which can model the battery more physically. Although it will increase the computational complexity, compared with the traditional equivalent circuit model, it can reflect more ageing mechanisms [77,78]. The method based on the equivalent circuit model is to estimate the SOH by looking up the table or regression

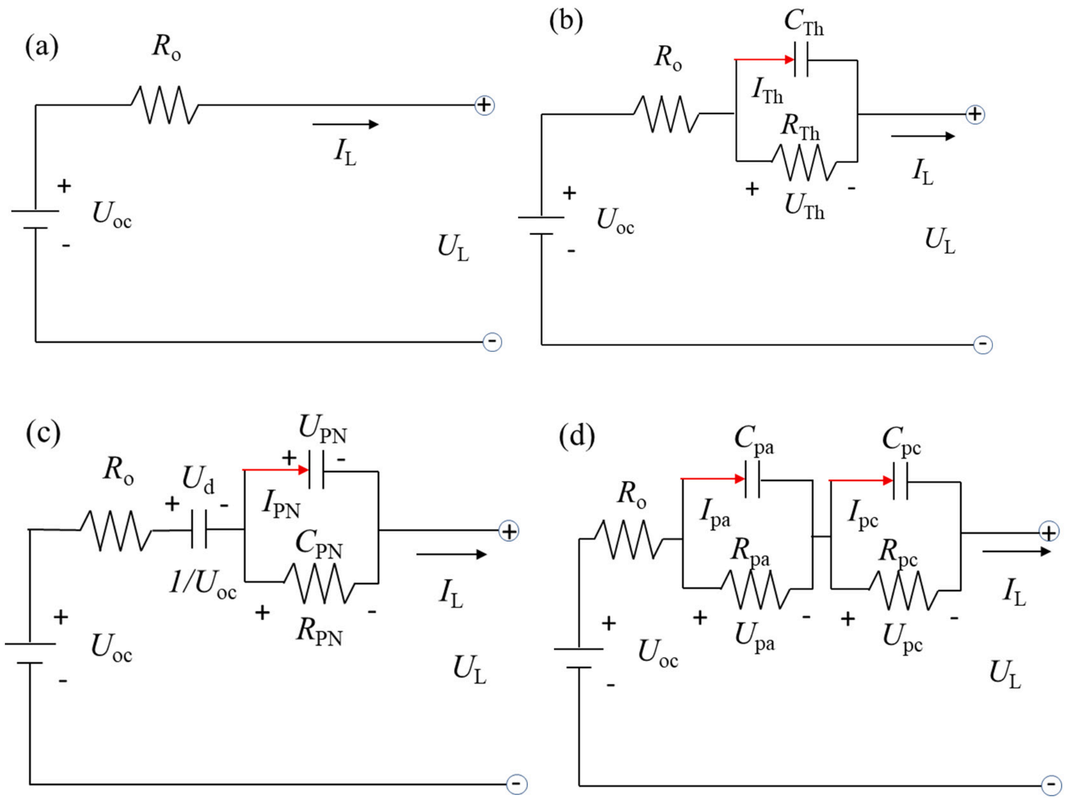

Fig. 7. Equivalent circuit model structure diagram [74]: (a) Rint model; (b) Thevenin model; (c) PNGV model; (d) n-order RC model.

by identifying the parameters in the model. This method often requires experimental calibration in advance, and it is difficult to cover all possible situations. Model-driven methods will have a better RUL prediction effect under the premise of accurate model establishment. However, the establishment of an accurate model depends on the working conditions of the laboratory, the calculation process is usually complicated, and the difficulty of parameter estimation is also very high. Therefore, it will affect the prediction accuracy of the application in the actual operating conditions of electric vehicles.

3.2. Prediction method based on data-driven

The data-based prediction method overcomes the shortcomings of experiment and model-based, and has a good predictive ability for time-varying signals. In recent years, there have been more and more lithium-ion battery life prediction methods based on machine learning and deep learning tools [35]. The most prominent ones include artificial neural networks [35,79,80], support vector machines (Support Vector Machine, SVM), correlation vector machines (Relative Vector Machine, RVM), and particle filters (Particle Filter, PF). SVM is a commonly used machine learning technique that is often used for pattern identification and classification problems [81]. SVM is used as a regression tool in several lithium-ion batteries remaining life prediction algorithms. Support Vector Regression (SVR) [82] is a variation of the methodology that these methods implement. SVM was employed in some early studies to estimate battery SOC [82,83]. Deep learning models and shallow machine learning models are two types of data-driven approximate models. According to the strength of the model's learning ability, the combined technologies can be subdivided into the following categories.

(1) Statistical techniques

The lifespan of each battery varies and is a random variable. After analyzing the probability distribution of capacity by mathematical statistics, the least squares method can be used to fit the probability distribution curve, and then the coupling relationship between capacity and life can be calculated [84,85]. Thereby, the prediction of the remaining life of the battery is realized.

The derivation expression between the remaining capacity of the battery and the life R is [86]:

$$R = t_0 - \frac{1}{\lambda} \bullet lna \tag{3}$$

In the formula: t_0—the time required for the battery from the beginning to full capacity; λ—the parameter that the remaining capacity obeys the distribution; *a*—the specific value set based on experience.

A large number of experimental results show that the capacity of the battery decays exponentially. The residual capacity decay curve is shown in Fig. 8.

Fitting Fig. 1 into the corresponding mathematical expression is:

$$P_m(X) = b_0 + b_1x^1 + b_2x^2 + \cdots + b_nx^k \tag{4}$$

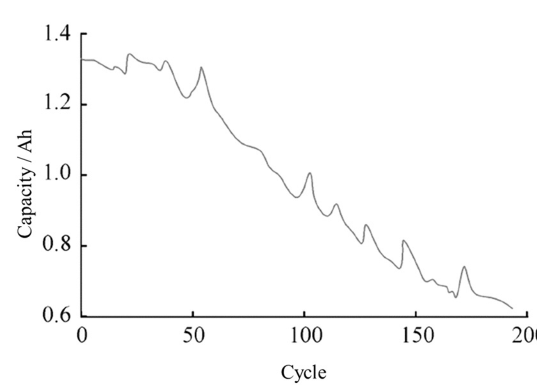

Fig. 8. Remaining capacity decay curve.

Calculate the line difference D at a node in the curve as:

$$D = P_m(x_i) - Z_i \tag{5}$$

In the formula: $P_m(x_i)$ is the fitting value of the residual capacity corresponding to the point x_i of the curve; Z_i is the real value of the residual capacity corresponding to the point x_i of the curve.

To achieve the minimum line difference, the partial derivative of the square sum of the line difference can be obtained and the partial derivative can be set to 0, that is

$$\frac{\partial Y}{\partial b_i} = 0 \tag{6}$$

where: Y is the sum of squares of line differences; b_i is the i coefficient of the polynomial of the capacity decay curve.

Solving this system of linear equations yields the polynomial coefficients, which in turn yield the derivation formula for battery life prediction. The prediction results can be easily obtained by using the curve fitting method, but such methods cannot be used in the case where the data matrix is irreversible, so there are certain limitations.

Autoregressive statistical models (Autoregressive Model, AR) and their variants (Autoregressive Moving Average, ARMA and Autoregressive Integrated Moving Average, ARIMA) generally deal with time series problems by establishing linear models, and treat future state values as linear functions of past state values and random errors [87]. Long et al. [88] suggested a lithium-ion battery RUL prediction approach based on an AR model. For the RUL prediction of lithium batteries, Liu et al. [89] developed a Nonlinear Negenerate Autoregressive (ND-AR) time series model with regularized PF to deal with the uncertainty problem. Zhou et al. [90] used the ARMA model in the RUL prediction of lithium batteries, combined with Empirical Mode Decomposition (EMD) to separate the global degradation trend and the SOH to obtain RUL and SOH.

Kalman Filter (KF) and PF are also two very important statistical methods. They are useful not just in RUL prediction of mechanism models, but also in data-driven techniques [91,92]. The idea of KF is to use known data to predict future data, as shown in Fig. 9, but the noise effect must be Gaussian noise. Due to the addition of the noise factor, it is closer to the reality than the Markov Model (MM), and the predicted curve is more consistent with the actual curve. He et al. [93] developed a method in line with the Unscented Kalman Filter (UKF), while Yan et al. [94] proposed an extended Kalman filter in line with Lebesgue sampling to estimate the RUL of lithium batteries (LS-EKF). Particle filters were used by related researchers to boost prediction accuracy even further.

The idea of the PF algorithm comes from the Monte Carlo idea. In simple terms, the frequency of the event is used to approximate the probability of the event. The main advantage of PF is that it can predict future related data with current data, and the data distribution can be arbitrary, not limited to Gaussian distribution. It is more in line with the actual relevant situation than the KF, as shown in Fig. 10. Hu et al. [95] integrated PF technology with the Kernel Smoothing (KS) approach to predict lithium battery RUL. The proposed method can simultaneously estimate the degradation model's deterioration status and unknown parameters. Through experiments, the proposed method performs better than the traditional PF method. Zhang et al. [96] proposed an improved unscented PF (Improved Unscented Particle Filter, IUPF) based on the Markov Chain Monte Carlo (MCMC) lithium-ion battery RUL prediction method. MCMC is used to solve the problem of sample impoverishment in the UPF algorithm. Su et al. [97] presented an IMMPF (Interacting Multiple Model Particle Filter) for lithium battery RUL prediction. The proposed approach offers greater accuracy than the standard PF. In 2017, Zhang et al. [98] proposed a new UPF for the RUL prediction of lithium batteries. Compared with the traditional PF, the prediction results are more accurate. To forecast the RUL of lithium batteries, Yu et al. [99] suggested a particle filter PF based on the Quantum Particle Swarm Optimization (QPSO) algorithm and compared it to the classic PF approach in the light of the particle swarm optimization PSO algorithm. It produces more significant results in comparison. Ma et al. [100] suggested a Gauss-Hermitian Particle Filter (GHPF)-based RUL prediction method for lithium batteries. The proposed approach offers greater accuracy than the standard PF.

In addition, there are other statistical methods. For example, Thomas et al. [101] constructed a statistical model based on data from accelerated ageing trials. According to big data statistical approaches, Zhao et al. [102] created a unique method for defect diagnostics of electric car battery systems. Ng et al. [103] suggested using a lithium-ion battery deterioration model based on Naive Bayes (NB) to forecast RUL at varied current rates and ambient temperatures.

(2) Stochastic technique

The cumulative damage process of random variables with a joint multivariate Gaussian distribution is known as the Gaussian Process

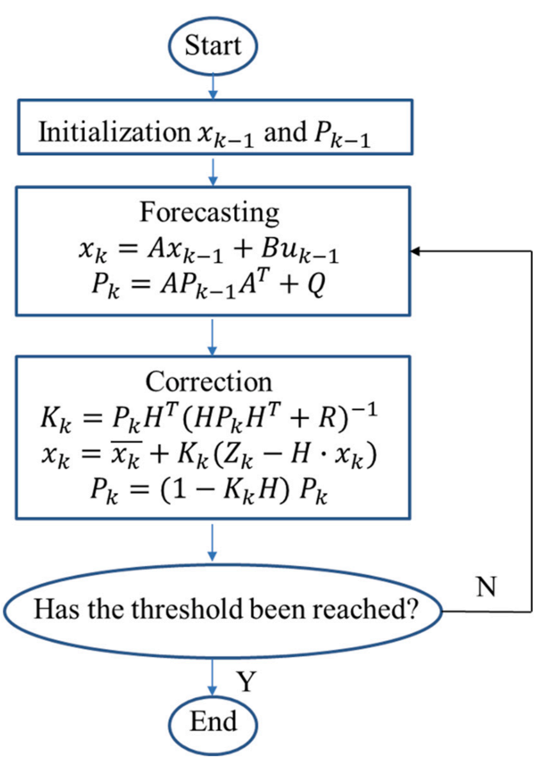

Fig. 9. Kalman filter algorithm steps.

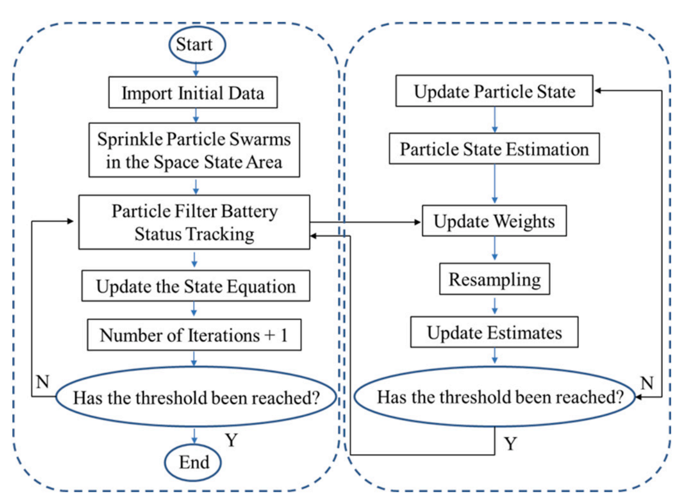

Fig. 10. Particle filter algorithm battery life prediction steps.

(GP). He et al. [104] developed a multi-scale Gaussian Process Regression (GPR) for lithium battery RUL prediction. The results of the experiments suggest that it outperforms classical GPR. A new RUL prediction approach based on Gaussian Process Mixture (GPM) was proposed by Li et al. [105]. Its main idea is to fit different trajectory segments to different GPR models to deal with multi-modal problems.

Moreover, GPM can also generate confidence intervals for predictions. Experiments have also demonstrated that the proposed approach outperforms classical GPR. Liu et al. [106] used Gaussian process regression GPR to capture the underlying trend of SOH, including general capacity decline and local regeneration.

Brownian motion is described by the Wiener process, a mathematical model. It is commonly used as a Markov process and a random process model. Tang et al. [107] used the Wiener Process with Measurement Error to construct a new RUL prediction method (WPME). The RUL degradation model in the literature can be expressed as the formula (7) [108]:

$$Y(t) = X(t) + \varepsilon = \lambda t + \sigma_B B(t) + \varepsilon \tag{7}$$

Among them, $Y(t)$ represents the degradation stage with measurement error, $X(t)$ is the degradation step without measurement error, ε is the measurement error, and λ represents the drift parameter. σ_B is the diffusion parameter, and $B(t)$ is the standard Brownian motion. RUL is predicted using a truncated normal distribution with the drift parameter's uncertainty and the distribution. To improve parameter assessment efficiency, maximum likelihood assessment is used. The model's usefulness is demonstrated through a variety of situations. The random approach allows for a more accurate assessment of lithium-ion battery health decline. However, successful prediction remains a challenge when the system takes into account the functions of random current, temperature changes, and self-discharge characteristics.

(3) Intelligent algorithm

Wu et al. [109] suggested an online model that simulates the link between the battery charging curve and the RUL under constant current using a Neural Network (NN). Although the prediction effect of NN is auspicious, its calculation amount is large, and the problem of local optimality will appear. Support Vector Machine (SVM) avoids the problem of NN local optimization and shows better performance. The benefit of SVM is that it simply requires a small amount of training data. The support vector obtained by SVM training determines the amount of calculation, which reduces the problem of dimensional disaster to a certain extent. The support Vector Regression (SVR) technique was employed by Patil et al. [110] to obtain accurate RUL prediction while the battery was reaching its end of life. For the RUL prediction of lithium batteries, Wang et al. [111] developed an iterative multi-step prediction model based on SVR and a non-iterative prediction model based on Flexible-Support Vector Regression (F-SVR). Low-dimensional data is used as input to get good prediction results. Klass et al. [112] proposed the application of SVM to the lithium battery RUL prediction of electric vehicles, and the proposed method is suitable for airborne applications of lithium batteries with processing capacity and memory constraints. Li et al. [113] applied SVM to the RUL prediction of lithium batteries. It has higher accuracy and less calculation through experimental comparison than traditional neural network prediction. To predict the RUL of lithium batteries, Zhao et al. [114] introduced two novel health indicators, the Time Interval of an Equal Charging Voltage Difference (TIECVD) and the Time Interval of an Equal Discharging Voltage Difference (TIECVD), which they paired with feature vector selection and SVR. Although SVM (or SVR) performs well, it is not suitable for processing big data, and the estimate of RUL is a point estimate. The RVM introduced next not only requires a short training time but also the obtained RUL estimate is a probability estimate, which related researchers have favoured.

To forecast the RUL of lithium batteries, Widodo et al. [115] employed the Sample Entropy (SE) feature of the discharge voltage as the input of RVM. Hu et al. [116] proposed a sparse Bayesian learning strategy that uses charging voltage and current as the input of RVM to assess the RUL of lithium batteries for implantable medical devices. The proposed method performs well in real-time RUL prediction. Liu et al. [117] developed a (Health Indicators) HIs extraction and optimization framework that only requires lithium-ion battery operating parameters for battery degradation modelling, using RVM as RUL estimation. Wang et al. [118] suggested a capacity degradation model based on the RVM method for predicting the RUL of lithium-ion batteries, and the findings were promising. Using intelligent algorithms such as machine learning to predict RUL is the most commonly used method in data-driven methods. In most cases, it has achieved better results than statistical techniques. However, most of these methods lack the analysis of the uncertainty of the forecast results.

(4) Deep learning model

Although the above three types of methods are widely used in the RUL prediction of lithium batteries, they cannot process a large amount of data, which limits their application in reality. Deep learning methods have gradually emerged in recent years, which possess considerable advantages in processing big data.

Recurrent Neural Network (RNN) has unique advantages in processing time series data, and RNN can store previous information in the memory unit and apply it to related tasks. Liu et al. [119] used lithium battery impedance spectroscopy data to input into an adaptive RNN to predict RUL Li-ion batteries. Eddahech et al. [120] applied RNN to the lithium battery RUL prediction of electric and hybrid vehicles and achieved good results. Although RNN performs well, it is difficult to solve the problem of gradient disappearance and gradient explosion caused by its network structure. Related researchers have focused on its variant Long Short-Term Memory Networks (LSTMN).

LISTEN to process all information through the gate structure. The function of the forget gate is to decide whether to retain information, the function of the input gate is to update the cell state, and the function of the output gate is to determine the value of the next hidden state. The gate mechanism of LSTMN avoids the problems of gradient disappearance and gradient explosion. Zhang et al. [121] introduced an RUL prediction approach based on the LSTMN model of a long and short-term memory network, which they validated through experimental data from several Li-ion batteries at varying currents and temperatures. The model does not rely on offline training data. A more satisfactory RUL prediction result was obtained.

DNN is a fundamental deep learning model. Khumprom et al. [122] used a deep neural network (DNN) to predict the battery's SOH and RUL. They combined it with other machine learning algorithms like Linear Regression (LR), k-Nearest Neighbors (k-NN), and Support Vector Machine (SVM). The results were superior to those of the Artificial Neural Network (ANN). Although the deep learning model can process big data and has a more vital learning ability than the shallow model, it also lacks the analysis of the uncertainty of the prediction results.

SVM was used by Klass, Behm, and Lindbergh [123] to estimate the status of health (SOH). They calculated battery voltage as a load current and state of charge (SOC). In the virtual test, the author employed the SVM model to estimate the battery's internal resistance and then used it to measure SOH. Klass, Behm, and Lindbergh [112] improved on previous work by including temperature dependency in the model. A virtual test, which can be used as an indicator of internal resistance and SOH, can also be used to evaluate battery capacity. Patil et al. [110] suggested a real-time RUL estimation approach for lithium-ion batteries based on SVM machine learning technology's classification and regression properties. By evaluating lithium-ion battery measured data in various working situations, extracting essential characteristics from the voltage, current, temperature curve, and other data in the data, and then using these features for model training, the lithium-ion battery RUL prediction aim can be achieved. To enhance the precision of SOH estimation, Dong et al. [76] used a fusion method in which a battery model trained using SVM is combined with a particle filter architecture. For RUL assessment, other approaches [68,118,124] use the probability feature of SVM termed Relevance Vector Machine (RVM). The Bayesian inference will be utilized to estimate RVM parameters in this situation, and the resulting model will be put into the particle filter framework for RUL estimation. Particle swarm optimization [125], Gaussian process regression [106], recursive neuro-fuzzy systems [126], genetic algorithms [127] based on the method of sample entropy [115,128], the naive Bayes model [103,129] and other geometric methods [130] are some of the alternative applications of machine learning methods for battery state estimation.

Hu et al. [131] suggested a data-driven prediction model incorporating sample entropy and a sparse Bayesian prediction model. Song et al. [132] developed a hybrid method combining the Improved Nonlinear Degradation-Autoregressive (IND-AR) model and the particle filter algorithm to forecast the remaining life of lithium-ion batteries during cycling, with promising effects. Wu et al. [109] used an Importance Sampling(IS) and Feed Forward Neural Network (FFNN) to assess the battery terminal voltage curve in different charging cycles and present an online approach to assess the RUL of Li-ion batteries. Cheng et al. [133] proposed a strategy based on Bayesian lithium battery RUL prediction and Functional Principal Component Analysis (FPCA). The FPCA method is utilized to create the lithium-ion battery deterioration model, and the model parameters are updated using the Bayesian model. RUL projections for lithium-ion batteries must be met. Hong et al. [134] suggested an Ensemble Empirical Mode Decomposition (EEMD) and Gaussian Mixture Model (GMM)-based bearing performance degradation evaluation approach. To anticipate the decline of lithium batteries, Saha et al. [40,135] used the battery's internal parameters to create a Relevance Vector Machine (RVM) model using a particle filter approach to estimate the adaptive parameters of the RVM model. However, the RVM algorithm's poor long-term forecasting capability makes it hard to get a good RUL estimation result with only the RVM model. By analyzing the patterns of several detection parameters, Lu et al. [130] discovered four geometric characteristics that are susceptible to lithium battery degradation from these figures. They have had much success when used as detecting criteria to define the degeneration of lithium batteries. To anticipate battery RUL, Kozlowski [70] suggested a data-driven prognostic technique that includes three variables to consider: Autoregressive Moving Average (ARMA), neural network, and fuzzy logic. These predictors are trained using battery data sets of the same size and chemistry subjected to various load scenarios.

On the other hand, collecting training data that covers all potential loading circumstances can be time-consuming and costly. Ng et al. [103] looked at the impact of ambient temperature and discharge current values on battery RUL and suggested a naïve Bayes model predict battery RUL under various working conditions. Liu [117] et al. suggested an improved Relevance Vector Machine (RVM) algorithm that may increase the accuracy and stability of RUL estimation while also providing an uncertainty representation. The Adaptive Recurrent Neural Network (ARNN) algorithm was utilized by Liu et al. [119] to anticipate the dynamic system state. The ARNN algorithm evaluated the RUL of lithium-ion batteries using the Recurrent Levenberg Marquardt (RLM) method to correct the weight of the RNN architecture in many places. The outcomes were satisfactory. Ren et al. [136] proposed ADNN, an integrated deep-learning method for forecasting the life of lithium batteries that combines autoencoder and DNN. This method is used to estimate how long several lithium-ion batteries will last. As shown in Fig. 11, the proposed method is applied to the accurate lithium-ion battery cycle life data from NASA. Experimental results show that the proposed method can improve the accuracy of RUL prediction.

Currently, several methods for estimating the RUL of lithium-ion batteries rely on very rigid usage circumstances, each with its own set of benefits and drawbacks in terms of application. The model-based method has the advantage of using fewer data to build the deterioration model, and the model's forecast is more accurate. However, the disadvantage is that accurate physical model are often required to describe the degradation process of lithium-ion batteries. This requires adding more expert knowledge, the model's versatility is limited, and the generalization effect cannot be determined. The analysis of the degradation process needs to consider some physical characteristics. Prediction usually has the defects of many model parameters and difficulty in practical application. It is also subject to noise and other external influences, and it is hard to track the load's dynamic properties. The dynamic accuracy, robustness and adaptability are poor and often too complicated to implement. Data-driven approaches are more adaptable than model-based methods and do not require a higher level of professional knowledge description. Thanks to the technology's continued growth, deep learning's application range has grown in recent years. The deep learning approach is relatively straightforward, and the generalization is extreme compared to the driving method. A well-trained model can predict most batteries, and the prediction effect is also better. As a result, in recent years, deep learning approaches have increasingly become the mainstream life prediction method.

Compared with the method based on mechanism analysis, the above-mentioned data-driven method usually requires a large amount of offline data, especially the capacity decline data of lithium batteries, to train the model and then use the trained model to achieve RUL

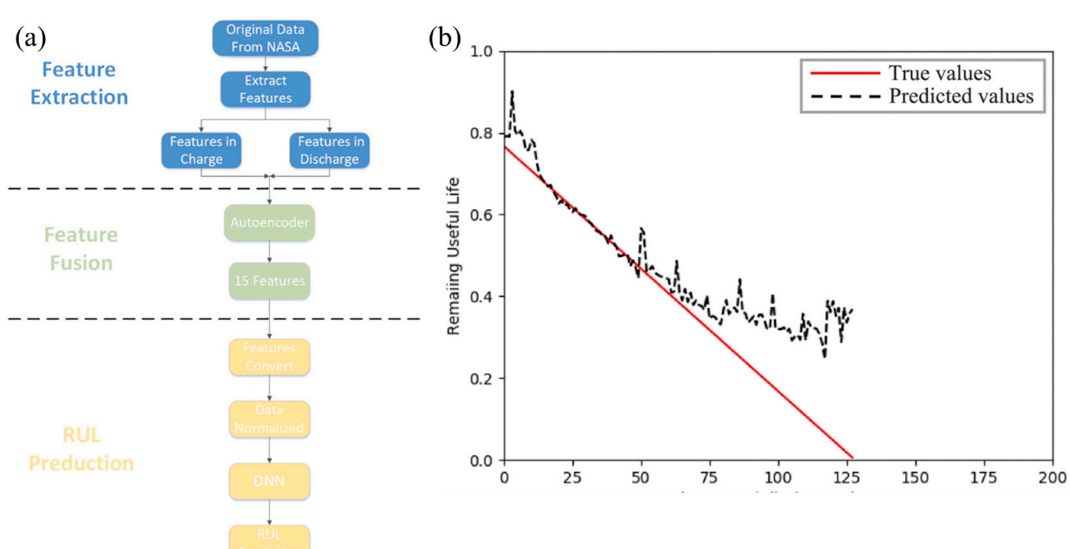

Fig. 11. (a) Deep learning framework for RUL prediction of lithium-ion batteries; (b) Prediction results after 40 cycles of ADNN [136].

prediction. These techniques can only be used for RUL prediction when the applied battery is working under stable charging and discharging conditions. Offline data for training is required to be collected from ageing experiments under similar operating conditions. However, the working conditions of the lithium battery in the application, including load current, temperature and SOC, etc., are all dynamically changing. Under a specific test condition, the lithium battery is subjected to a cycle life test from a new state to the end-of-life test time, Generally more than 6 months. Therefore, in practice, the offline capacity degradation data that can be collected for training is limited, which limits the application of these data-driven methods in RUL prediction. Accurate lithium battery capacity estimations are first required to obtain enough capacity degradation data for model training. Based on the estimated battery lifespan capacity degradation data, relevant mathematical transformations are performed, and a linear model is established to predict the battery RUL further. Data-driven methods are highly accurate but have poor applicability to different batteries and are highly dependent on the sampling frequency and completeness of the collected data.

3.3. Fusion method

The fusion method, combined with different methods, aims to overcome the limitations of various single methods to improve the accuracy of diagnosis and prediction by better using all available information. Fusion methods can be classified into two categories: those based on filtering techniques (Kalman filter, particle filter, and variants) and those based on intelligent algorithms such as machine learning.

The Lithium Battery RUL prediction fusion approach presented by Liu et al. [137] combines the Extended Kalman filter EKF with the Nonlinear Scale Degradation Parameter based Autoregressive (NSDP-AR) model, which is based on the Kalman filter framework. There is also an RUL prediction method proposed by Zheng et al. [138] based on a nonlinear time series prediction model and the Unscented Kalman filter UKF algorithm. UKF and short-term capacity recursively update the battery model's state. The proposed model verifies higher accuracy and reliability than EKF. For lithium battery RUL prediction, Song et al. [139] coupled RVM and KF. Because RVM has great short-term predictions but poor long-term predictions, they developed an iterative updating approach to enhance the long-term forecasting accuracy of battery RUL projections. To predict the RUL of lithium-ion batteries, Chang et al. [140] integrated the unscented Kalman filter UKF, Empirical Mode Decomposition (EMD), and relevance vector machine RVM. Another fascinating study [141] uses Brownian motion technology to estimate battery RUL by combining a Kalman filter and a Gaussian distribution state space.

Compared with Kalman filtering, the fusion method of the PF technical framework has been favoured by more researchers. Dong et al. [142] integrated the Brownian Motion (BM) deterioration model with PF to forecast the RUL of lithium batteries. This method outperforms the Gaussian process regression method in terms of performance and predictability. Zhang et al. [143] used the exponential model and the PF algorithm to forecast the RUL of lithium batteries, which is more accurate than other algorithms like the Auto-Regressive Integrated Moving Average model (ARIMA). Guha et al. [144] coupled the empirical model with PF for the RUL prediction of lithium batteries. Dong et al. [76] developed a fusion approach combining SVR and PF for RUL prediction of lithium batteries, and the experimental results obtained are better than the typical single PF. Song et al. [132] suggested a hybrid technique combining the IND-AR model with the PF algorithm that is ideal for nonlinear deterioration estimates and can improve lithium battery long-term RUL prediction performance. Li et al. [145] combined Gaussian Process (GP)and PF, used data fusion under different conditions as the input of GP model distribution learning, and finally used PF to complete the prediction of the RUL of lithium batteries. Zhang et al. [146] used a combination of RVM and PF to forecast the RUL of lithium batteries. The proposed method can decrease the training data to 30 % of the total degradation data, reducing overall time. Another fusion strategy is to replace the mechanism model of the state equation or measurement equation representing the system's dynamic behaviour in the EKF or PF algorithm with a suitable data-driven model. For example, Charkhgard and Farrokhi [147] proposed a combination of EKF and offline training neural networks, while Daroogheh et al. used a particle filter instead of EKF [148]. In addition, Bai et al. [79] designed a new battery model based on an artificial neural network and combined it with KF. These methods are based on the following considerations: The mechanism-based model and the alternative model need to identify appropriate model parameters based on available observation data. However, the analysis and derivation of the machine model are very time-consuming, and the alternative model does not require any mechanism analysis and derivation. The calculation speed is usually faster, especially for the numerical model, which is particularly suitable for real-time applications [149]. Cadini et al. [150] used particle filtering and Multi-Layer Perceptron (MLP) neural networks to propose a real-time RUL prediction framework, where MLP is used to replace the observation equation of PF.

Many fusion methods are also based on intelligent algorithms such as machine learning. Yang et al. [151] used a combination of RVM and associated physical models to forecast lithium battery RUL. Hu et al. [152] presented their research on lithium-ion battery failure prediction in implanted medical devices, which used a hybrid data-driven and mechanism model approach for life prediction. It has two modules: a data-driven module that uses sparse Bayesian learning to infer capacity from charge-related features and a recursive Bayesian filtering module that updates the empirical capacity decay model (mechanism model module). He et al. [55] developed a double exponential empirical degradation model based on DS theory (Dempster-Shafer Theory, DST) and Bayesian Monte Carlo (BMC) to predict RUL, and DST was used to initialize training data. Set parameters, then utilize BMC to update the model's parameters. There are other methods to predict RUL by using Nonlinear Least Squares(NLLS) to estimate the parameters of the battery's mechanical degradation model [153,154]. Lei et al. [136] combined Auto Encoder (AE) and DNN to perform RUL prediction of lithium batteries. Autoencoder AE is used for multi-dimensional feature extraction, and DNN is used for RUL prediction of multiple sets of lithium batteries.

Peng et al. [155] employed a combination of the Wavelet Denoising (WD) approach and the Hybrid Gaussian Process Function Regression (HGPFR) to estimate RUL on lithium batteries, with WD being used to minimize noise. The experiment shows a lower root mean square error value than the HGPFR model, indicating that the proposed strategy is effective. As shown in Fig. 12, the effects of this and HGPFR models with different training data lengths on the prediction results are compared and analyzed. Based on the database of the Department of Engineering Sciences (DES) of Oxford University and the Center for Advanced Life Cycle Engineering (CALCE) of the University of Maryland, the numerical simulation results are analyzed. For the data repository, an accuracy of 2.2 % is obtained compared with the same value of 6.7 % for the HGPFR model. The prediction results verify the applicability and stability of the method. Some methods use intelligent optimization algorithms to optimize the parameters of the prediction model. For example, Chen et al. [156] devised a quantitative method for predicting RUL based on the Adaptive Bathtub-shaped Function (ABF). The normalized capacity prediction curve and historical experimental data back up the proposed model. The Artificial Fish Swarm (AFS) algorithm was used to estimate the ideal parameters of the ABF curve, which resulted in a more accurate forecast. Long et al. [88] employed the particle swarm optimization PSO approach to enhance the AR model's important parameters and applied it to lithium battery RUL prediction.

In summary, the fusion prediction method for lithium-ion battery RUL has progressively become the industry standard and is one of the most important research topics in this sector [146,157,158]. Since it is difficult to accurately predict the nonlinear variation of SOH through the

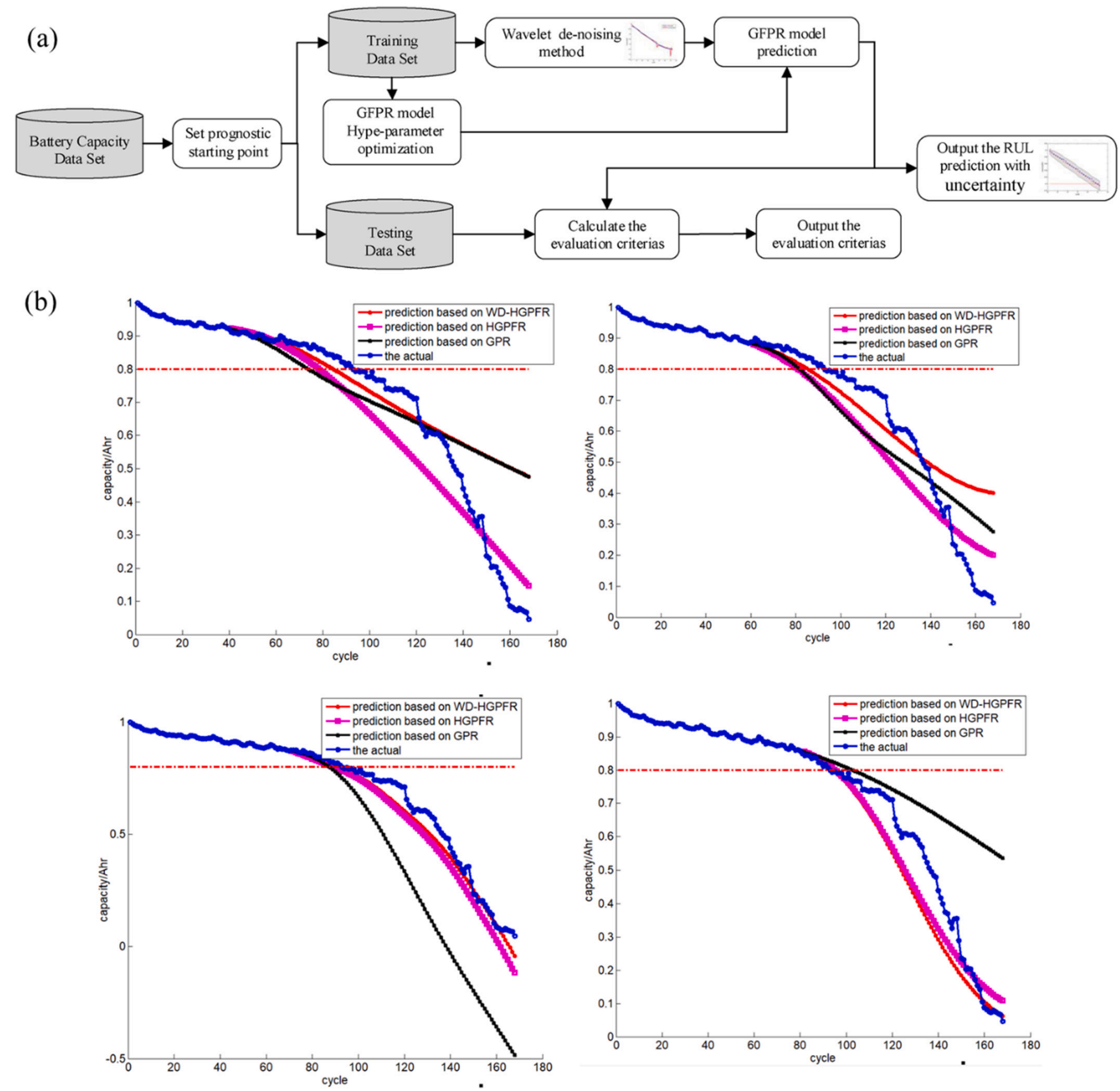

Fig. 12. (a) Fusion method of wavelet denoising (WD) method and mixed Gaussian process function regression (HGPFR) model; (b) Comparison of the influence of HGPFR models with different training data lengths on the prediction results [155].

capacity degradation process, a SOH prediction method is different from the direct use of capacity data. Examples include discharging to a fixed cut-off voltage and combining conductance technology with other measurement parameters (such as battery temperature and power). In addition, based on the new HI, an extreme learning machine (ELM) is proposed to realize the RUL prediction of lithium-ion batteries. However, the above method does not conduct an in-depth analysis of the temperature change characteristics that also impact the battery capacity degradation process.

4. Challenge

.First, the data-driven model is constructed based on battery historical degradation data. The advantage is that it does not require complex expression formulas to demonstrate the actual mechanism of the battery. The model is less complicated and easier for practical applications. The disadvantage is that constructing a high-precision model necessitates a vast amount of previous data. The mechanism model can comprehend the battery's physical laws and provides a precise formula for expressing the battery's degrading process. The advantage is higher accuracy, but the disadvantage is highly complex. The mechanism analysis and derivation require a lot of calculation time and resources. In most circumstances, establishing an accurate mechanism model is complex. Although fusion methods can address the flaws of numerous single methods, the majority of fusion methods still rely on battery mechanism models.

We compare the advantages and disadvantages of many lithium-ion battery RUL prediction methods, as shown in Table 2. Each method has

Table 2
Comparison of various data-driven RUL prediction methods.

Model	Advantages	Disadvantages
AR	• Simple and universal.	• Without considering the influence of external factors; • The predicted result is a point estimate.
KF	• Strong robustness, taking into account the influence of noise.	• Only Gaussian noise is considered; • The influence of past data on future prediction results is not considered.
PF	• Forecast results have the ability to express uncertainty.	• Requires battery empirical degradation model.
GPR	• Suitable for processing high-dimensional and small sample data; • Better short-term forecasting effect.	• Poor long-term forecasting effect; • Past data cannot be used.
Winner	• It can simulate non-monotonic processes by adding random noise.	• A deviation from the actual situation; • Past data cannot be used.
SVM	• Simple model; • Small calculation; • Faster training speed.	• The result of the prediction is point estimation, which cannot handle large amounts of data.
RVM	• The model is simple, and the predicted result is interval estimation.	• Cannot handle a large amount of data; • The accuracy of the prediction is related to the selection of the kernel function.
RNN	• Can process time series data and store past information in memory cells.	• Complicated and computationally expensive network model; • The problems of gradient disappearance and gradient explosion are prone to occur.
LSTMN	• Can process time series data and solve the problem of gradient disappearance and gradient explosion of RNN.	• Complexed network model; • Large calculation; • Long training time.
DNN	• Have the ability to deal with non-linear and high-dimensional data.	• Large calculation; • The problem of local optimization will occur.
Fusion model	• Two or more combined approaches have higher prediction accuracy than a single model.	• The model is more complicated and the amount of calculation becomes larger.

its advantages and disadvantages. Among them are two types of mainstream lithium-ion battery RUL prediction methods. One is based on filtering technology [43,48,98,159] (such as particle filter or Kalman filter technology) fusion battery mechanism degradation model or empirical degradation model RUL prediction method. The other is the RUL prediction method based on data-driven machine learning models [10,109,114,116] (such as correlation vector machines, support vector machines, or neural network models). These two types of RUL prediction methods have advantages and are widely used, but there are still some problems. Firstly, the RUL fusion prediction method based on filtering technology relies on the battery mechanism degradation model or empirical degradation model; Second, the RUL prediction method based on the machine learning model is primarily a single model RUL prediction method, whereas the capacity degradation process of Li-ion batteries is relatively complicated, and the RUL prediction method based on a single model has poor prediction performance; Thirdly, shallow machine learning models have limited nonlinear fitting capabilities for battery capacity degradation processes. RUL prediction methods based on shallow machine learning models have insufficient long-term prediction capabilities, and some methods lack uncertainty management. The introduction of a deep learning model with a solid nonlinear fitting ability also has insufficient battery capacity degradation data samples, leading to overfitting the deep learning model.

The issues of RUL prediction for lithium-ion batteries based on PHM can be summarized as follows:

a) There is a problem with insufficient battery capacity degradation sample data since the number of single cells tested at the same temperature and under the same conditions is minimal. The problem of insufficient data volume increases the difficulty of the data-driven RUL prediction task;

b) The battery capacity degradation curve is a nonlinear degradation process with a downward trend, first slow and then fast. For the data-driven RUL prediction method, if only the early degradation trend data is used for life prediction, there will inevitably be significant errors;

c) Partial capacity regeneration will occur during the entire battery capacity degradation process. This causes the degradation curve not to be monotonously decreasing, and the degradation curve fluctuates wildly.

d) Description of lithium-ion batteries' thermal, electrical, and ageing coupling behaviour under complex stress factors. Lithium-ion batteries' thermal, electrical, and ageing behaviours are coupled and affect each other, making accurate system modelling quite challenging. In the future, it will be critical to create efficient and accurate intelligent decoupling approaches and investigate the transferability and hierarchy between external stress, internal parameters, and external behaviour using theoretical methods such as system identification and state estimation. Clarify the relationship between the dynamic behaviour of heat, electricity, and ageing. Establish a thermal-electricity-ageing coupling model for lithium-ion batteries under complex stress factors. Combine nonlinear observers and adaptive filters to form a high-precision and robust lithium-ion battery system and a thermal, electrical, and ageing coupling behaviour description system.

This challenges the data-driven RUL prediction model to fit the capacity degradation trend. All these complex capacity degradation features add difficulty and challenges to the data-driven RUL prediction task. The degradation process of the battery capacity of lithium-ion batteries shows a nonlinear trend under different use environments and working conditions. An accurate capacity prediction can keep the battery system stable for a more extended period. Through the analysis of the advantages and disadvantages of different methods, it can be seen that the accuracy of the battery modelling determines the prediction accuracy of the method based on the machine model. The results predicted by RUL have higher accuracy on the premise that the model is accurate. However, the degradation process of Li-ion batteries is nonlinear. Various electrochemical reactions take place inside it. The model parameters are difficult to identify, and the degradation period is extended, requiring much prior knowledge. It is more complex and time-consuming to model. The model established by the mechanism model method has poor universality, and the prediction accuracy will be significantly affected as the battery's ambient temperature, and operating conditions change.

Data-driven methods require less prior knowledge. The internal laws are mined by analyzing the historical charge and discharge data of lithium-ion batteries. The model complexity is low and can be applied to practical situations. For example, the cascade utilization of energy storage systems, new energy vehicles, etc., has unique advantages in battery life prediction. At the same time, a complex modelling process is not required, and the generalization is strong. The prediction accuracy is high, and the model established for a single battery can be extended to similar batteries. However, the disadvantage is that it often only considers the discharge process of the battery, lacks consideration of the battery charging process and temperature changes, and requires more battery degradation data to train the model.

5. Summary

There have been many studies on capacity prediction, and relatively ideal prediction results have been achieved. However, the degradation process of the capacity itself is not monotonous with the continuous progress of battery charging and discharging; side reactions in the battery increase. The reaction product is deposited near the electrode, causing the internal resistance to increase, resulting in a gradual decrease in the battery's usable capacity as the number of cycles on the battery grows. However, when the battery is resting after the charge and discharge, the reaction products near the electrode will have the opportunity to dissipate, which can increase the available capacity in the next cycle and cause a short-term recovery of the capacity. This phenomenon is the self-recovery phenomenon of capacity. Because the existence of the self-recovery phenomena will influence the battery's average deterioration trend, the lithium-ion battery's RUL prediction will indeed affect the prediction accuracy. In addition, this self-recovery capacity phenomenon must exist during each battery's everyday use. Therefore, it is necessary to consider the self-recovery of capacity when conducting RUL prediction of lithium-ion batteries. Most current studies are based on the relationship between capacity and charge-discharge cycle life to establish a model, considering the overall trend of overall degradation, to obtain an approximate “smooth” capacity decay model. The self-recovery phenomenon of capacity is often neglected. The experimental results obtained from this and the actual degradation data often do not fit closely, and the accuracy of the prediction results is not high enough. Therefore, it is still challenging to predict the RUL of lithium-ion batteries considering the self-recovery effect of capacity.

The large-scale application of lithium-ion batteries in various fields puts forward high requirements for their reliability and safety, making the remaining life prediction of lithium-ion batteries a research hotspot. Presently, related fields have carried out more research on the life prediction of lithium-ion. Model-driven approaches, data-driven methods, and fusion methods of two can be loosely split into three groups for estimating the life of lithium-ion batteries. The purpose of the model-based method is to model the battery and simulate its behaviour. However, this method often relies too much on experience, and the model's generalization is not strong. Traditional data-driven methods are not good enough for prediction accuracy. Although the fusion method combines the advantages of the two, because the model is more complex, the amount of calculation becomes larger. More research and optimization of the prediction approach will be required to investigate lithium ion life prediction further.

In the future, more abundant research can be carried out in the following aspects:

(a) The simulation experiment under the charging state is not carried out in modelling the battery's external characteristics. The input of the LSTM model considers voltage and current and does not consider the effect of different ambient temperatures. Future work can consider temperature as the input of LSTM to study the model's generalization ability to different ambient temperatures.

(b) Feature selection. When extracting features from the battery's voltage-capacity curve, due to the computational and storage constraints of the battery management system. Many factors affect the SOC and SOH of lithium batteries, and they are not limited to external data such as current, voltage, and temperature that are easy to measure. If valuable parameters can be extracted from the electrochemical reaction mechanism inside the lithium battery, it will be a work of great research value. Future work can consider reducing the amount of data for feature extraction while ensuring the model's accuracy.

(c) The data sets used in the current experiment are mainly the data set of a battery factory, the MIT-Stanford data set and the Cambridge data set. In addition to the DC impedance test and impedance spectrum test, the data of these batteries are all cycle tests of constant current-constant voltage and 100 % depth of charge and discharge. However, the working modes of electric vehicles and grid energy storage are different from the laboratory mentioned above test modes. Therefore, future work needs to consider the verification of actual operating conditions.

(d) Many lithium battery SOC and SOH prediction methods are only simulated on the computer using offline lithium battery data. The model has not been transplanted to the hardware system or the Internet of a Vehicles cloud platform for online testing. Therefore, transplanting the prediction method to the battery management system or the Internet of Vehicles cloud platform will become the direction of continued efforts in the next step.

In summary, the RUL prediction of lithium-ion batteries is a critical technology that can effectively avoid serious problems caused by battery failure or failure, and the attenuation of the capacity itself has a partial self-recovery effect, so this review focuses on considering the self-recovery effect of the capacity Research on RUL prediction of lithium-ion batteries. A more profound capacity decline model is established through a more profound analysis of the capacity to achieve a more accurate lithium-ion battery RUL prediction, improve the safety and reliability of battery applications, and save costs.

Since machine learning has entered the process research stage, building an autonomous, universal, multi-regional, cross-seasonal, multi-mode and long-term vehicle battery operating condition database is necessary. Research on machine learning algorithms to better promote battery state estimation includes evaluating the cost and robustness of different algorithms, enhancing the practicability of machine learning algorithms, determining the hyperparameters of machine learning algorithms according to data characteristics, and enhancing the generality of machine learning algorithms.

CRediT authorship contribution statement

Kai Song；Die Hu；Yao Tong；Xiaoguang Yue Conceptualization, Methodology, Software；Data curation, Writing - Original draft preparation；Visualization, Investigation；Supervision；Writing - Reviewing and Editing.

Declaration of competing interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled-Remaining life prediction of lithium-ion batteries based on health management: a review.

Data availability

No data was used for the research described in the article.

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