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Review on Prediction Methods of Remaining Useful Life of Lithium Ion Batteries

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Abstract: *Compared with other types of ion batteries, lithium-ion batteries have great advantages in specific capacity, self-discharge rate, performance and price. Therefore, lithium-ion batteries have developed rapidly and are widely used in aerospace, portable equipment and so on.The rul prediction method of lithium-ion battery is developing from experimental reliability to practical reliability, expanding the application scope of the prediction method and ensuring reliable ex ante maintenance, which can not only ensure the safety of personnel, property and equipment in civil use. There are two main methods for rul prediction of lithium-ion battery: one is to build a capacity decline model based on the internal electrochemical mechanism of the battery, Due to the complex internal chemical mechanism of the battery, the differences between the same batch of batteries lead to its application limitations; The second is the data-driven method. Through the extraction of parameters in the process of battery operation, such as voltage and current, support vector machine, artificial neural network and other methods are used for prediction. From the prediction results, the data-driven method has high precision and wide application. It is the mainstream research method at present.It is of great significance to accurately determine the health status of lithium-ion batteries. To address the problem that the prediction of a single limit learning machine algorithm is prone to jumping, the method of using artificial fish swarm optimization to optimize the limit learning machine is proposed to try its best to predict the model of the remaining life of lithium-ion batteries. Firstly, the isovoltage discharge time is extracted as an indirect health factor, then the limit learning machine is optimised using the artificial fish swarm algorithm to build an indirect prediction model for the remaining life of Li-ion batteries, and finally a validation evaluation is carried out based on the NASA dataset B0005-B0006. The experimental results show that the proposed model predicts stable prediction results with high accuracy and small error in prediction results.*

Keywords: *Lithium-ion batteries; Remaining useful life; Physicochemical model; Data driven method*

1. Introduction

Lithium ion battery was proposed by M. S. Whittingham in the 1970s. Because of its great advantages over other types of ion batteries in specific capacity, self discharge rate, performance and price, it has developed rapidly and is widely used in aerospace, portable equipment and so on. At present, the state strongly advocates that new energy vehicles contribute to energy conservation and emission reduction, and lithium-ion batteries are widely used in new energy vehicles. In addition, compared with vehicles powered by fuel, new energy vehicles have less infrared exposure symptoms and noise, so they are also widely used in military equipment, such as position reserve power supply, missile launcher, etc. Although the lithium-ion battery has outstanding advantages, like other rechargeable batteries, it has the problem of capacity attenuation, and the safety performance of the battery will decline. Since 2021, Tesla electric vehicles have been out of control and hit roadside obstacles, causing fires, indicating that there are still hidden dangers in the safety performance of lithium batteries, especially on May 10, 2021, In a community near Chengnan interchange, Chenghua District, Chengdu, the battery car in the elevator caught fire, resulting in many injuries, including a 5-month-old baby girl. According to China's requirements and test methods for cycle life of power batteries for electric vehicles, the test shall be stopped when the actual effective capacity of the battery is 80% lower than the initial value, because the battery is in an unstable state at this time, For example, the loss of recyclable lithium, SEI film decomposition, electrolyte decomposition and electrode loss of the battery. If the battery continues to work, it will lead to equipment damage and battery deflagration, resulting in casualties. Therefore, it is necessary to accurately determine the working state of the battery

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and replace the battery when it is about to fail. Especially in the military field, it is necessary to manage the whole life cycle of each part to ensure the safe and reliable operation of the equipment. Therefore, the capacity attenuation and remaining useful life (rul) prediction of lithium ion batteries need to be deeply studied.

2. Research Status at Home and Abroad

The life of lithium-ion battery is divided into calendar life and cycle life. Scholars at home and abroad generally study the cycle life. Cycle life refers to the number of cycles when the battery capacity declines to 80% of the initial capacity under certain conditions [4]. So far, the remaining service life of lithium-ion batteries has been realized through algorithms and modeling. From the existing literature, the methods applied in this process can be divided into three categories: model-based methods, data-driven methods and fusion based methods [1-3]. The model-based method obtains the model by analyzing the internal mechanism of lithium-ion battery and equivalent its working circuit. The data-driven method simulates the internal mechanism of the battery by establishing a black box model, which does not require researchers to have professional battery knowledge. The fusion based method predicts the life of lithium-ion battery through the fusion of model and data-driven or between data-driven, so as to make up for the shortcomings of different methods. At present, data-driven and its fusion methods are the focus of lithium-ion battery research. The rise of artificial intelligence and machine learning improves the accuracy and speed of rul prediction. As shown in Figure 1, it is the main research method for rul prediction of lithium ion battery.

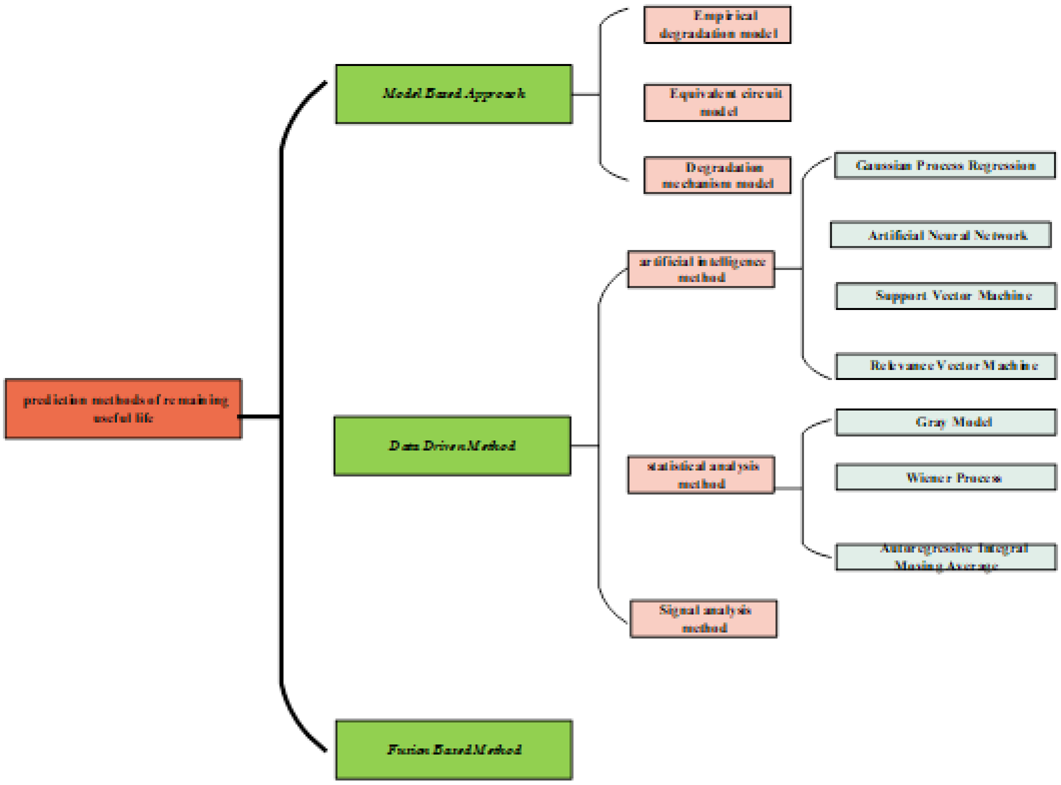

Figure 1 main research methods for rul prediction of lithium ion battery

2.1. Model Based Approach

The model-based method is to establish the battery cycle degradation model based on the internal chemical mechanism of the battery. It is the earliest and highly reliable battery rul prediction method, mainly including empirical degradation model, equivalent circuit model and degradation mechanism model.

2.1.1 Empirical Degradation Model

The empirical degradation model does not directly reflect the battery structure and internal

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mechanism, but based on statistical analysis, a statistical model of approximation law is established by mining the internal relationship between input and response output. Rul prediction based on empirical model is mainly predicted by combining empirical model and filtering algorithm. At present, the filtering algorithms used mainly include Kalman filter and its improved algorithms, particle filter and its improved algorithms.

Kalman filtering (KF) is an algorithm that uses the linear system state equation to optimally estimate the system state through the system input and output observation data. Since the observation data includes the influence of noise and interference in the system, the optimal estimation can also be regarded as a filtering process [5].

Particle filter (PF) is a recursive filter using Monte Carlo method. It represents the posterior probability of random events through a group of weighted random samples (called particles), and estimates the state of dynamic system from noisy or incomplete observation sequences [6].

Wang Haixia et al. Proposed a method for lithium ion battery life prediction based on extended Kalman filter [7]. Duong P et al. [8] Aiming at the problem of sample degradation and impoverishment in particle filter, introduced heuristic Kalman algorithm, a meta heuristic optimization method, combined with particle filter to solve sample degradation and impoverishment. Aiming at the low accuracy of particle filter and traceless particle filter, Qiu x et al. Proposed the backward smooth square root volume KF algorithm, and then used multi-scale hybrid KF to jointly estimate the battery health state and charge state, which improved the accuracy, confidence and resampling rate of estimation [9].

Aiming at the problem that the selection of PF importance function and the decline of sampling particle diversity limit the estimation accuracy, Heng Zhang et al. Proposed an traceless particle filter algorithm based on linear optimization combined resampling [10].

Based on KF, PF and related improved algorithms, it has high accuracy in battery rul prediction, but its prediction results can not accurately track the change of battery capacity. In particular, capacity regeneration is common in lithium-ion batteries. Therefore, in order to improve the traceability of predicting degradation trajectory, The sliding window grey model is used to update the state variables of the state space model in the traceability prediction model, so that the model can track the capacity change more accurately [11]. However, in the above literature, the tracking of capacity change trend by the proposed method has deviated in the later stage, because the change of battery capacity is closely related to its working mode, so the tracking results will deviate. At present, the battery health monitoring is not only to obtain the rul of the battery, but also to track the capacity in real time. Therefore, the battery rul prediction based on the empirical degradation model can not meet the demand.

2.1.2 Equivalent Circuit Model

Equivalent circuit model is to replace or transform complex circuits or concepts with simple circuits or known concepts based on expert knowledge in order to simplify circuit analysis while keeping the working output effect of the circuit unchanged, so as to achieve equivalent or approximate effect. This physical idea or analysis method is called "equivalent" transformation. At present, there are mainly rint model, resistance capacitance model [12], PNGV model, CPE model, tanh model, etc., of which rint model and resistance capacitance model are the most widely used models.

Xiaosong Hu et al. Compared and analyzed 12 models, and determined the optimal model parameters of two lithium-ion batteries based on multi swarm particle swarm optimization algorithm to realize battery state estimation [13]. In order to establish a battery model with sufficient accuracy and appropriate complexity, Hongwen he et al. Proposed an equivalent circuit model with two RC networks by analyzing shepherd model, rint model and DP model [14]. In order to improve the accuracy of the model in the application of dynamic load, wladislaw waag et al. Used the parameterization technology of impedance and adopted additional weighting coefficients in the complex nonlinear least squares fitting process. This method effectively reduced the uncertainty of dynamic battery voltage response [15].

Compared with the empirical degradation model, the equivalent circuit model can adapt to a certain extent, but it can not solve the relationship between the complex environment inside the battery. It is difficult to load the factors of the external environment into the model. The scope of application is relatively harsh, resulting in the poor ability of the battery to adapt to the changeable battery working conditions.

2.1.3 Degradation Mechanism Model

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Degradation mechanism model obtains various factors affecting battery aging attenuation by analyzing the basic principle of battery work. Generally, the charge and discharge model of single battery is established based on the empirical model of battery, and then the aging law of battery is coupled into the charge and discharge model of battery through some relevant parameters, so as to establish the mechanism model of battery aging. In recent years, the degradation mechanism models of lithium-ion batteries mainly include the mechanism model of solid electrolyte interface (SEI) membrane, the first principle model and the complex electrochemical model with many influencing factors.

Qi Zhang et al. Considered that the formation, development and extinction process of SEI film is an important factor of capacity degradation, and proposed a single particle model to simulate the cycle data of lithium-ion battery [16]; GK Prasad et al. Proposed an electrochemical model that depends on two key aging parameters, which change monotonically with time, fitting the recognized attenuation mechanism of lithium battery [17]. Anil v. virkar et al. Considered the chemical potential, SEI film and other factors, modeled the aging process, and finally obtained the battery health state and service life state [18]. S ánchez Luciano et al. Proposed the method of semi physical model, combined with the theory of empirical fuzzy logic, which improved the accuracy of open loop model [19].

Rul prediction based on degradation mechanism model can directly reflect the degradation of relevant physical and chemical processes in the battery. However, a lot of parameter estimation is required. If the battery electrode material, service environment and working conditions need to be added, its dynamic tracking ability is poor. At the same time, the added parameters increase the complexity of model establishment. Therefore, the method based on degradation mechanism is not suitable for on-line estimation, battery pack module and complex battery working conditions.

To sum up, although the model-based method relies on expert knowledge and can establish a model in line with the battery performance attenuation through the analysis and modeling of the electrochemical principle of lithium battery, there are many limitations in practical application. First, it is necessary to model different types of batteries, and there will be internal differences in the same batch of batteries; Second, there are many parameter estimation and high complexity; Third, the online capacity tracking of lithium-ion battery can not be realized and the capacity regeneration is poor. Therefore, the performance of the model-based method is poor, and a simpler method is needed to predict the rul of lithium battery.

2.2. Data Driven Method

Based on the analysis of the internal mechanism of lithium-ion battery, the model has a theoretical basis to judge whether the battery life reaches the end point when judging the remaining service life of the battery. However, the model is established for different types of batteries, and the efficiency is not high. The data-driven method can make up for these shortcomings, that is, using the relevant data generated during the operation of lithium-ion battery, such as voltage, current, temperature and other parameters, build the health factor predicted by rul, analyze the change trend of capacity through the health factor, and obtain the capacity decline curve. So far, there are three main data-driven methods: artificial intelligence, statistical methods and signal processing. These methods can be divided into direct prediction and indirect prediction according to health factors.

Rul prediction of battery based on artificial intelligence method

2.2.1 Gaussian Process Regression

Gaussian process regression (GPR) is a nonparametric model for regression analysis of data using Gaussian process (GP) a priori. The rul prediction of lithium ion battery based on GPR does not need to be combined with the actual battery model, but uses Gaussian process to simulate the battery behavior. It is a probabilistic prediction method.

RR Richardson et al. Proposed using Gaussian process regression to predict the life of lithium-ion battery; Pang Jingyue et al. [14] used Gaussian process regression to predict the capacity of lithium-ion battery. Aiming at the problems of difficult direct measurement of capacity and uncertainty of prediction expression in online residual life prediction of lithium-ion battery, a method framework for constructing residual life prediction health factors by using lithium-ion battery charge and discharge monitoring parameters [20]. Zheng Xueying et al. [21] regarded the energy regeneration as the energy highlight of the capacity attenuation process of lithium-ion battery, and used the empirical mode decomposition method to obtain the energy distribution of the sample. Aiming at the problem that the capacity regeneration phenomenon affects the accuracy of rul prediction modeling of lithium-ion battery, an energy weighted GPR method based on empirical mode decomposition was proposed, The experimental results show that this method has higher accuracy and adaptability than the basic GPR algorithm, and the root mean square error (RMSE) of single-step prediction and multi-step prediction are reduced by 3% and 10% respectively. However, from the actual operation results, the multi-step prediction error is still large, which can not meet the needs of practical application, and needs to be improved.

Although the accuracy of rul prediction of lithium-ion battery based on GPR method is improved, the error of multi-step prediction is still large, some parameter settings and adjustments are complex, the amount of calculation is large, and the ability of on-line prediction is lack.

2.2.2 Artificial Neural Network

Artificial neural network (ANN) is a research hotspot in the field of artificial intelligence since 1980s. It abstracts the human brain neural network from the perspective of information processing, establishes a simple model, and forms different networks according to different connection modes. In engineering and academic circles, it is often directly referred to as neural network or quasi neural network. Neural network is an operation model, which is composed of a large number of nodes (or neurons) connected with each other. Each node represents a specific output function, which is called excitation function. The connection between each two nodes represents a weighted value for the signal passing through the connection, which is called weight, which is equivalent to the memory of artificial neural network. The output of the network varies according to the connection mode of the network, the weight value and the excitation function. The network itself is usually the approximation of some algorithm or function in nature, or the expression of a logical strategy.

Multilayer feedforward neural network trained by BP neural network learning algorithm is the most widely used type of neural network. Zhang Jinguo and others proposed to establish a life prediction model based on BP neural network analysis method. On the basis of the prediction model, the average influence value algorithm is used to screen the input parameters of the model [23]. Parthiban et al. Chose a neural network, which has an input layer, a neuron corresponds to an input variable, i.e. cycle (charge discharge cycle), and an implicit layer composed of three neurons, which is output to the output layer through the activation function. The output layer is composed of two neurons, representing charge and discharge capacity respectively, and its activation function is also a sin type transfer function, The results show that the discharge characteristics of lithium-ion battery are in good agreement between the calculated capacity value and the observed capacity value [24]. Akram eddahech et al. Proposed a method for monitoring the behavior and health status of lithium-ion batteries using impedance spectroscopy and cyclic neural network, established a model by using the method of equivalent circuit, considered several important internal phenomena of lithium batteries, and used recursive neural network to predict the deterioration of battery performance, covering the whole process from modeling to predicting performance degradation and use [25]; Yongzhi Zhang et al. Proposed a long short term memory (LSTM) based recurrent neural network to predict the remaining service life of lithium-ion battery. The elastic mean square back propagation method is used to adaptively optimize the LSTM recurrent neural network. The developed method can predict the rul of battery independently of off-line training data, and when some off-line data are available, Rul can be predicted earlier than traditional methods [26].

However, there are still some problems in using ANN method to predict battery rul: ANN method needs a large number of data sets when training the model, consumes a long training time, and the effect of the model is positively correlated with the amount of data. More data will cause over fitting of the model, and less data will cause under fitting of the prediction results.

2.2.3 Support Vector Machine

Support vector machine (SVM) is a kind of generalized linear classifier for binary classification of data according to supervised learning. Its decision boundary is the maximum margin hyperplane for solving learning samples. SVM is applied to pattern recognition problems in various fields, including portrait recognition, text classification, handwritten character recognition, bioinformatics, etc. [28-29]. Wang Yixuan et al. Proposed the prediction of battery life based on improved support vector machine, and optimized the penalty coefficient and super parameters of support vector regression machine by using immune complete learning particle swarm optimization algorithm to enhance its prediction ability [30]. As a novel artificial intelligence technology, least squares support vector machine (LS-SVM) has been more and more widely used in various disciplines [31]. Sheng Hanmin and others proposed that based on the regression principle of least square SVM (LS-SVM), the LS-SVM model

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was constructed by extracting the external characteristics during the operation of lithium battery, and particle swarm optimization (PSO) was introduced to improve the training efficiency and model accuracy [32]. Xie Bing et al. Established the life prediction model of lithium-ion battery based on LS-SVM to predict the residual capacity of lithium-ion battery. At the same time, the genetic annealing algorithm can effectively improve the prediction accuracy and generalization ability of the model [33]. Wang Xueying and others optimized LS-SVM parameters by using the improved bird swarm algorithm. The test results show that the model has good prediction effect and stability for the remaining life of lithium-ion battery [34].

SVM method does not produce the problem of local minimum, only needs a small number of samples, and can obtain high accuracy and good convergence. However, it is difficult to select its kernel function and lacks the expression and management of uncertainty.

2.2.4 Relevance Vector Machine

Correlation vector machine (RVM) is a sparse probability model similar to SVM proposed by micnacl E. tipping in 2000. It is a new supervised learning method. RVM has higher sparsity and can provide probability prediction.

Datong Liu et al. Proposed an optimized correlation vector machine algorithm based on incremental learning to estimate the remaining service life of lithium-ion battery. Zhao et al. Proposed a fusion rul prediction method based on deep belief network and correlation vector machine, and took the last hidden layer of deep belief network to generate the training data of RVM model. Liu Yuefeng et al. Proposed a method to integrate multiple kernel functions to build correlation vector machine prediction model [37] because of the large subjectivity in the selection of kernel functions, resulting in the limited performance of the constructed prediction model. Aiming at the problems of long training time, difficult parameter determination and unstable output results in the process of lithium-ion battery life prediction, He Wei et al. Proposed to use RVM with better generalization ability, sparser, shorter test time and more suitable for on-line detection for prediction, and optimized the correlation vector machine through excessive sub particle swarm optimization to ensure the stability of prediction output results.

RVM algorithm for rul prediction can avoid over fitting, has better generalization performance, and can perform interval estimation and point estimation. However, on the one hand, the long-term prediction accuracy using RVM algorithm is low; On the other hand, because the RVM correlation vector is more sparse than the support vector, and the capacity data fluctuates to some extent, the stability of estimation usi

Statistical methods a statistical model is established based on empirical knowledge and existing data to predict the degradation trend of battery capacity. In the probability framework, the random coefficient model or random process model is constructed based on the historical measurement data to describe the battery capacity decline. Because it does not rely on expert knowledge, the statistical modeling method is easy to implement. The statistical method can effectively describe the uncertainty of battery degradation and provide accurate rul prediction results. The main statistical methods are: grey model, Wiener process, autoregressive integral moving average.

2.2.5 Gray Model

The grey system theory was proposed by Deng Julong in 1982 and can solve the problems of small samples and low information [44]. Grey model is one of the most widely used grey prediction models.

Weijun Gu et al. Proposed a new accelerated life test method for lithium ion battery life evaluation system based on grey system theory. Without reducing the number of test items pre specified in the accelerated life test plan test matrix, a grey model for predicting the cycle times of specific life end indicators was established [45]. Dong Zhou et al. Based on the online prediction of the remaining service life of lithium-ion battery based on the optimized grey model, extracted a new health from the operating parameters of lithium-ion battery for degradation model and rul prediction [46].

Grey model has advantages in solving the problem of small samples, but due to the regeneration of battery capacity data, the application of grey model has limitations, that is, it can not deal with non smooth data.

2.2.6 Wiener Process

Wiener process is an important independent incremental process, also known as Brownian motion process. In mathematics, Wiener process is a continuous time random process, named after Norbert

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Wiener. Because it is closely related to Brownian motion in physics, it is often called "Brownian motion process" or "Brownian motion".

Based on the Brownian motion model and particle filter, Guang Dong et al. Considered the influence of the moving distance of Brownian particles on the capacity in a given time interval, and then used PF to estimate the drift parameters of Brownian motion. Guang Jin et al. Proposed a rul prediction method based on damage marker bivariate degradation model. From the prediction results, this method is suitable for short-term prediction, and the long-term prediction deviation is large.

2.2.7 Autoregressive Integral Moving Average

Stationary linear stochastic processes can be represented by a small number of autoregressive terms and moving average terms. For non-stationary stochastic processes, the differential integrated moving average model (ARIMA) can be approximated by a high-order AR model. Because the computational efficiency of AR model is higher than ARIMA model, AR model is usually used for battery rul prediction. Bing long et al. Proposed an improved autoregressive model for lithium-ion battery prediction based on particle swarm optimization, established an AR model based on the capacity attenuation trend of lithium-ion battery, analyzed the shortcomings of the traditional AR model sequencing criteria, and proposed a new method of root mean square error as the order of AR model. Then particle swarm optimization algorithm is used to search the order of the optimal AR model [50]. Chen Yanyu et al. Took the cyclic residual capacity data as the time series sample and established the autoregressive moving average (ARMA) prediction model for each decomposed sub series based on empirical mode decomposition, which has high accuracy in long-term prediction. When using this method, the time series needs to be stable and the battery runs early. Due to the small amount of data, the model can not be used and has great limitations.

2.2.8 Prediction of Battery Remaining Service Life Based on Signal Analysis Method

The capacity data of lithium battery is non-stationary signal, which contains various effective and useless information. Accurately distinguishing these information can be more convenient in battery rul prediction. Various signal processing methods are used to extract useful information from the original data for diagnosis and prognosis. Signal processing methods are an important tool for battery data processing, Rul prediction can be realized through the processed data.

Chen Yanyu and others use empirical mode decomposition to decompose the battery capacity data to obtain components, predict and stack the components in decibels, and can also achieve high-precision rul prediction of lithium battery. Yujie Wang proposed a model free rul prediction method based on discrete wavelet transform. In these literatures, many battery capacity components are obtained, and it takes a long time to predict each component, and the effect of this method based on a small amount of data is poor, that is, it can not realize the early prediction of battery rul, so it needs to be improved.

To sum up, the application of data-driven methods is relatively mature. In essence, the model construction is based on the data of battery operation. When non capacity data is used as the health factor, it is indirect prediction, and when capacity data is used as the health factor, it is direct prediction. These two methods can accurately predict the battery rul without expert knowledge. However, The extraction of health factors is affected by operating conditions and environment, and the scope of application is slightly limited. There are still shortcomings in later and early prediction, which need to be improved.

2.3. Fusion Based Method

The fusion based method combines different methods to make up for the deficiency of different methods in predicting rul of lithium-ion battery and obtain higher accuracy. It includes the fusion between model-based methods, data-driven methods and data-driven methods. Zhang Ning et al. Proposed a simple and effective rul prediction method based on the integration of model method and data-driven method. In this method, through the fusion of model method and data-driven method, the double exponential empirical degradation model is deformed to reduce the model parameters and the difficulty of parameter training. The process of battery capacity decline is tracked by particle filter algorithm; In order to improve the prediction accuracy, the autoregressive (AR) time series model is introduced to modify the observed values of the state space equation [34]. Wei Qin et al. Take particle filter (PF) algorithm as the core, double exponential model as the state equation and artificial neural network as the observation equation. After the importance resampling process, the battery degradation

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curve is obtained after a posteriori parameters are obtained, and then the system rul is estimated [35]. Chang y et al. Combined the fragrance free Kalman filter algorithm, complete ensemble empirical mode decomposition and RVM algorithm, and proposed a new hybrid method with error correction idea to predict the rul of lithium-ion battery [36]. Hancheng Dong et al. Proposed to integrate particle filter and SVM algorithm to establish riul prediction model [37]. Compared with a single algorithm, the accuracy of these fusion methods is improved, but when the model is established, the complexity is high and the amount of calculation is large. The coupling degree based on the model and data-driven method is not high, so it can not realize online and real-time prediction.

3. Problems in Existing Research

Through the analysis and Research on the current situation of rul prediction methods for lithium-ion batteries, it is found that the current prediction methods have some limitations, especially based on the constant working condition data in the data sets of NASA and the University of Maryland, which is difficult to apply to the actual operating conditions. In addition, if rul prediction in the whole life cycle is to be realized, the scale of the early generated data must be expanded, To ensure that the data-driven method has enough training. Therefore, the research needs to overcome the following difficulties:

(1) Real time performance of rul prediction of lithium ion battery and improvement of capacity tracking ability in the middle and later stages of the model

(2) Increase the failure early warning and full life cycle capacity monitoring of lithium-ion batteries

(3) Facing the improvement of model prediction accuracy under different working modes

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