Data-driven prognostics and remaining useful life estimation for lithium-ion battery: A Review *

LIU Datong, ZHOU Jianbao, PENG Yu *

(*Department of Automatic Test and Control*, *Harbin Institute of Technology*, *Harbin* 150080, *China*)

Abstract: As an important and necessary part in the intelligent battery management systems (BMS), the prognostics and remaining useful life (RUL) estimation for lithium-ion batteries attach more and more attractions. Especially, the data-driven approaches use only the monitoring data and historical data to model the performance degradation and assess the health status, that makes these methods flexible and applicable in actual lithium-ion battery applications. At first, the related concepts and definitions are introduced. And the degradation parameters identification and extraction is presented, as the health indicator and the foundation of RUL prediction for the lithium-ion batteries. Then, data-driven methods used for lithium-ion battery RUL estimation are summarized, in which several statistical and machine learning algorithms are involved. Finally, the future trend for battery prognostics and RUL estimation are forecasted.

Key words: lithium-ion battery; remaining useful life; data-driven prognostics; hybrid approach

1 Introduction

The rapid advances of lithium-ion battery technologies have made them widely used in almost all of industrial fields, including electric vehicles, consumer electronics, communications, aviation, spacecrafts and so on. Compared with traditional NiMH and NiCd battery, the lithium-ion battery has the advantages of high output voltage, high energy density, low self-discharge rate, long cycle life, high reliability and safety[1-2].

Due to the importance of the lithium-ion batteries in various systems, a lot of fatal failures of complex systems are attributed to their battery sub-systems[3-4], thus, the reliability of lithium-ion batteries has attracted much attention of the electronics industry. With the challenges of safety management, charge and discharge control, and performance degradation, diagnostics and prognostics and remaining useful life (RUL) estimation for the lithium-ion batteries have become the hottest issues but the most challenging issues in the fields of power system, reliability engineering, system engineering, aerospace applications, etc. Accurate RUL prediction can help the maintenance schedule and optimize the repairs in advance and provide an alarm before degradation or failure reaches critical level. As a result, this intelligent function can prevent malfunction and catastrophic failures of battery systems. In the intelligent battery management system (BMS), the prognostics and RUL estimation is essential to meet the requirements on life extension, reliability testing and condition-based maintenance. In particular, lifetime tests and data modeling and analyzing should be carefully addressed for reliability evaluation and system maintenance.

In this area, the methods for battery RUL estimation can be generally classified into two categories: model-based and data-driven approaches[5-7]. Model-based method requests the mathematical ex-

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pressions or the mapping of the system and the physical model. The advantage of model-based method lies in that it can obtain high performance for a more accurate RUL estimation. But model-based methods require the precise description of the electrochemical degradation process with the mathematical or physical or other models. At the same time, as a complex electrochemical system, it is very difficult to obtain a flexible and accurate model, or sometimes, it is hard to identify the applicable parameters for some existing models[8].

Compared with the model-based approach, the data-driven method only depends on the monitoring data and historical data, to realize degradation analysis and heath status assessment[9]. In recent years, the data-driven algorithm has become the mainstream of the RUL estimation. Many data-driven algorithms have been reported to estimate the RUL for the lithium-ion batteries. The key of data-driven algorithms is to establish a correlation model between the conditioned monitoring data and the expected RUL value. Although the data-driven methods obtain great success and apply widely in industrial applications, the prognostic process with data-driven method is usually opaque and such models are often invisible to the users. Due to the complex relationship between the state monitoring data and the system RUL, the RUL estimation still remains a challenging.

With the ahead mentioned development in data-driven approaches for the degradation modeling and RUL prediction of lithium-ion batteries, this paper focuses the status and advances in this area. The rest of this paper is organized as follows: in Section 2, the related definitions and concepts of health status and performance degradation for lithium-ion battery are introduced. Then, Section 3 mainly describes the methods for identifying and modeling the lithium-ion battery degradation. The widely applied data-driven approaches for lithium-ion batteries RUL estimation are analyzed and discussed in Section 4. Finally, Section 5 summaries the main challenges and future perspective.

2 Related definitions and concepts

Before we summarize the data-driven methods for battery RUL prediction, the related concepts and definitions are addressed at first.

1) Capacity: to indicate the capability of power storage and is measured in unit of amp-hour (Ah).

2) Rated capacity: to refer to the obtained capacity discharged to cut-off voltage at a constant current (discharged rate typically equals to 0.2C specified by the manufacturer).

3) Actual capacity: to refer to the maximum discharged capacity to fully discharge under certain conditions. It should be emphasized that the battery capacity and the remaining power is different.

4) Electrochemical Impedance Spectroscopy (EIS): is the response of a lithium-ion battery to AC signals of different frequencies, which can be obtained by applying the signals to a real electric circuit known as equivalent circuit constructed from circuit elements such as resistors and capacitors[10]. The ratio of AC voltage and current (regarded as the system impedance) changes with the different frequency ω, as a result, the Nyquist curve of the impendence can be obtained. By checking the Nyquist curve, we may analyze the influence on parameters of solution resistance, charge-transfer resistance and Warburg impedance with the cycle number.

5) Charge/discharge cycle: a charge/discharge cycle means charging and discharging for one time to the storage battery.

6) State of charge (SOC): is the equivalent of a fuel gauge for the battery pack, and the SOC are percentage points (0% = empty; 100% = full).

7) Depth of discharge (DOD): is an alternate method to indicate a battery´s SOC. The DOD is the complement of SOC, and the units for DOD can be Ah or percent points (100% = empty; 0% = full).

8) State of health (SOH): to indicate the condition of a battery compared to its ideal condi-

tions[11]. The units of SOH are percent points (100% = the battery´s conditions match the battery´s specifications). Typically, a battery´s SOH will be 100% at the time of manufacture and will degrade over time and usage.

9) Degradation: to indicate the process from health status to performance decrease until functional failure.

10) Health Indicator (HI): to evaluate the health status of a lithium-ion battery and represent the health level of the fade status and level[12].

11) Degradation state identification: to map the different parameters or variables into the health indicator, in order to determine the current health status of the lithium-ion battery.

12) Failure threshold: to define the battery´s performance or health status which can not continue to maintain the objective systems or equipments to work as the failure threshold. Generally, we define about 70% to 80% of the rated capacity as the failure threshold for lithium-ion battery, that may vary for different requirements and applications[13].

13) Life: includes three categories, that are storage life, usage life and cycle life. Storage life refers to the experienced time degraded to a certain degree for the battery performance in shelving/storage conditions. Usage life refers to the time period fading to the failure threshold under certain charge and discharge conditions. In actual applications, we usually apply cycle life to describe the life characteristics, that is, the charge and discharge cycles degraded to the failure threshold under certain charge and discharge conditions.

Therefore, the remaining use life referred to in this article is the remaining cycle life of the lithium-ion battery, which is the experienced cycles from this moment until the lithium-ion battery capacity cannot sustain the device working properly.

Figure 1 shows the degradation modeling and RUL estimation for a lithium-ion battery.

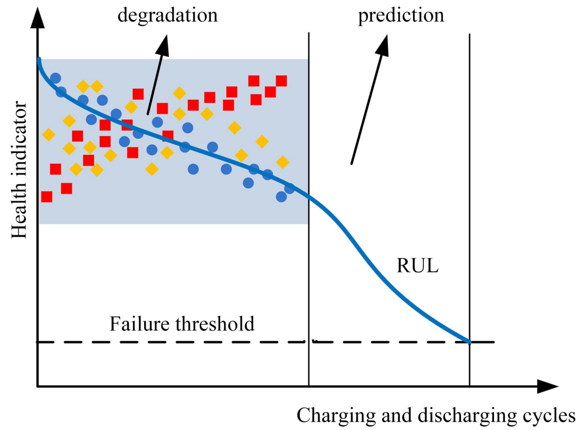

Fig. 1 Diagram of remaining useful life prediction for lithium-ion battery

3 Degradation identification for lithium-ion battery

The degradation state identification is the basis for RUL estimation, in which the health indicator is extracted and identified, used as the indicator to represent the RUL value.

3.1 Degradation parameters

Lithium-ion batteries store and release energy by the inside chemical reaction. With the evolvement of chemical reaction in actual applications, a series of aging phenomenon occurs in the internal lithium-ion battery, leading to gradually fading of their health status. The typical characteristics of performance degradation exhibit as the capacity fading or impedance increasing. Thus, the capacity and internal impedance is often adopted as the indicating parameters to assess the performance degradation of a lithium-ion battery.

1) Capacity

Nowadays, the battery capacity is always used for representing the health status, and the health status indicating with the capacity can be described as[11],

$$SOH=\frac{Capacity(k)}{Capacity(0)}\times 100\% \quad (1)$$

where $Capacity(0)$ is the initial capacity or rated capacity (Ah), $Capacity(k)$ is the actual capacity in the k^{th} cycle (Ah).

As the internal parameter, the battery capacity can not be measured directly, generally calculated with ampere-hour (ah, amp-hr) method[14]. The amp-hr method estimates the battery capacity by accumulating the discharging current, in which the lithium-ion battery is charged and discharged thoroughly under particular working conditions for the life test. However, this method is very time consuming for capacity estimation, at the same time, the life test in the laboratory experimental conditions is hard to cover all of the practical complex operating conditions. Moreover, in actual industrial application, the lithium ion battery is not working with fully charge and discharge. As a result, the amp-hr method is not so applicable and flexible.

2) Impedance

Currently, many scholars focus the battery health status in the view of impedance increasing, that includes AC impedance (referred to as impedance) and ohmic resistance (referred to as resistance).

It is reported that the lithium-ion battery capacity degradation is mainly caused by the increasing of AC impedance. Therefore, the impedance can describe lithium-ion battery health state, and it is proved that a linear relationship exists between the impedance and the capacity[15]. Thus, the lithium-ion battery capacity measurements can be converted to the measurement of battery impedance.

The key issue is how to obtain the impedance of lithium-ion battery while using impedance to describe the health status. Currently, the most commonly used approach to measure the battery impedance is the EIS test[16]. Saha et al. obtained impedance of lithium-ion batteries through EIS, and modeled the correlation relationship between impedance and capacity using support vector regression method. Based on the impedance, the SOH can be defined with power as,

$$SOH=\left(1-\frac{Power(k)}{Power(0)}\right)\times 100\% \quad (2)$$

where $Power(0)$ is the initial power or rated power (W), and $Power(k)$ is the available power after the k^{th} charging and discharging (W).

Gomez et al.[18] pointed out that the equivalent circuit model parameters EIS contains important battery information. Lee et al.[19] introduced that EIS test results can be used to estimate the battery capacity loss. Ran et al.[20] considered that the cell aging mechanisms can be studied through EIS. Kozlowski[21] achieved impedance spectroscopy using sinusoidal signal scanning methods based on second-order battery model, and integrated ANN, ARMA and fuzzy logic approach to assess the battery SOH.

The advantage of EIS method is that it can accurately obtain the impedance of the battery[22]. However, this method is a typical off-line method, and the EIS measurement is complex and time-consuming, which requires specialized testing instruments. To apply the EIS technology for on-line monitoring of battery status, is still a challenge and needed further study.

To overcome the difficulty for the EIS measurement, some researchers studied the correlation relationship between capacity and the ohmic resistance of lithium-ion battery, and proposed the SOH definition with ohmic resistance,

$$SOH=\frac{R_{EOL}-R}{R_{EOL}-R_{new}}\times 100\% \quad (3)$$

where R_{new} is the initial resistance, and R_{EOL} is the resistance of end-of-life, and R is the current resistance.

Ohmic resistance measurement is generally conducted as follows. A smaller load is adding into the circuit, and the change of the voltage for the load can determine the change of the internal resistance of the lithium-ion battery. The SOH is then calculated according to Eq. (3). Meanwhile, the battery ohmic resistance measurement requires that the battery is at it static status and with no connection with outside circuit. Moreover, the value of ohmic is very small which is typically milliohm, that make it hard to accurately measure. Therefore, Dai et al.[23] obtained the relationship of battery resistance and cycle numbers under different DODs, discharging rates, operating temperatures for lithium-ion batteries with the accelerated aging test. A function is established between the internal resistance and the battery model parameters, open circuit voltage of the battery. By using Dual EKF (Dual Extended Kalman Filter, DEKF) method, the battery resistance is estimated. But the disadvantage of this method is that the measurement of open circuit voltage of the battery must take a long static period of time (usually several hours), which limits its practical applications. Hu et al.[24] proposed a multi-scale EKF algorithm to achieve an accurate estimate of the battery SOC and capacity, which is more effective and accurate than the DEKF and Joint EKF. Liu[25] Combined the internal resistance and SOC, the SOH is predicted in real time via internal resistance estimation with the educed-order DEKF method, in which the main drawback is that accurate SOC estimator is needed.

3.2 Degradation idetification methods

1) Direct degradation identification methods

As mentioned above, we can obtain the degradation parameters, such as battery capacity, internal impedance, by direct test or measurement, which is called direct degradation identification method in this paper.

The advantage for these methods is that precise degradation parameters for health status assessment can be obtained. On the other hand, these parameters are all internal parameters inside the lithium-ion batteries, which can only be measured or estimated in certain experimental test in an off-line way. Moreover, the test is time-consuming, complicated, and high cost, that is not suitable for on-line applications.

2) Indirect degradation identification methods

To solve the difficulty in the test of battery capacity and internal resistance, some researchers extract and identify degradation parameters with available monitoring parameters. These degradation parameters can approximate the battery capacity or internal resistance for degradation modeling. Compared to the direct degradation identification methods, these methods to extract and identify the health indicators can be called indirect degradation identification method.

In actual applications, the available monitoring parameters include charging and discharging voltage, current, time intervals, temperature, etc. Widodo et al.[26] presented an intelligent prognostic framework for battery health assessment based on sample entropy (SampEn) feature of discharge voltage. The SampEn time series are extracted and used as health indicators. Then, the support vector machine (SVM) and relevance vector machine (RVM) methods are utilized to estimate the SOH. Liu et al.[27] analyzed the characteristics of discharging voltage during the degradation process for lithium-ion batteries, and proposed a novel health indicator for battery cycle life assessment. The grey correlation analysis is applied to evaluate the efficiency for time interval to equal discharging voltage difference (TIEDVD) series, which proved high similarity exists between the TIEDVD series and battery capacity series.

The degradation identification has great impact on the performance of RUL estimation for lithium-ion batteries. In this field, insufficient efforts have been made to extract and identify available and flexible and applicable degradation parameters for battery health assessment.

4 Data-driven approaches for remaining useful life estimation

4.1 Data-driven methods

Data-driven methods use the historical data or monitoring data to train prediction model, with which the RUL can be estimated. The main advantage of the data-driven method is that the modeling do not needed to consider the complex battery mechanism, which make it widely used and rapidly developed.

The data-driven methods include AutoRegressive (AR) model, Artificial Neural Networks (ANNs), SVM, Gaussian Process Regression (GPR), RVM, etc. we will briefly introduce these widely used data-driven methods for lithium-ion battery RUL estimation. One thing needed to be emphasized is that, in this paper, the statistical filter algorithms such as particle filter (PF), Kalman Filter (KF) are not involved.

1) AR model

A series of time series prediction models including AR, Moving Average (MA), AutoRegressive and Moving Average (ARMA) and their nonlinear improved models, e.g. AutoRegressive Conditional Heteroscedastic (ARCH), Generalized AutoRegressive Conditional Heterosecdastic (GARCH), Threshold AutoRegressive (TAR), etc.[28]. These AR series models predict the future state based on several past system states. In general, the ARMA model and MA model can be approximated with high order AR model, and the parameters identification for AR model is flexible and of high real time performance[29].

Saha *et al.*[30] used ARMA algorithm to model battery internal parameters and capacity, and the prediction is realized with extrapolation. To improve the nonlinear prediction capability of ARMA model for battery RUL estimation, Liu et al.[8,31] proposed an improved Nonlinear Degradation AR (ND-AR) model to track the accelerated factor, considering that the battery capacity degradation exhibits an acceleration phenomenon after the medium lifetime. Long et al.[32] adopted AR model to track the battery capacity degradation, in which the particle swarm optimization (PSO) algorithm is used to determine the order of the AR model, and a new error criteron is applied for AR model order determination.

The AR model is simple and flexible to use whose computation complexity is low. But these models lack of uncertainty representation and may not be suitable for complicated prediction.

2) ANN

The ANN algorithms are the most widely used prediction methods. Jon et al.[15] proposed a Double-Sigmoid Model (DSM) based on ANN to realize the cycle life prediction for lithium-ion battery. It is proved that the DSM can precisely estimate the remaining cycle life until the 50% performance degradation. Liu et al.[33] presented an Adaptive Recurrent Neural Network (ARNN) algorithm for state prediction of dynamic system. The ARNN algorithm uses the Recurrent Levenberg-Marquardt (RLM) method to adjust the weights of RNN architecture, and obtained satisfied results in the lithium-ion battery RUL estimation. Andre et al.[34] proposed a Structured Neural Network (SNN) algorithm with prior knowledge, to describe the mathematical function of battery voltage, current and resistance with the equivalent circuit. In SNN, the temperature, current and SOC are used as inputs and voltage is used as output, as a result, the interval resistance can be estimated to obtain the remaining cycle life for lithium-ion battery. Parthiban et al.[35] applied the ANN model to achieve life degradation prediction, in which the charging and discharging cycles are as inputs and the capacity is as output. The ANN architecture is that one input layer with one neuron corresponding to one input variable, and a hidden layer consisting of three neurons to generate their outputs to the output layer through a sigmoid function, and the output layer consists of two neurons, representing the charge and discharge capacity, whose activation function is also the sigmoid transfer function.

The traditional ANN mainly has two drawbacks that limit its applications, that are the network structure is complex and all the weights of ANN must be trained; and the training may lead to over-fitting and high computation.

3) SVM

On the basis of VC-dimension theory, the SVM can get global minimum using structural risk minimization as the optimal criterion. Especially, the SVR is suitable for the modeling of small samples. Rufus et al.[36] proposed a lithium-ion battery diagnostic and prognostic framework for space applications, using SVM for battery failure detection. At the same time, the Dynamic Neural Network (DNN) is utilized to explain the degradation process and estimate the RUL of lithium-ion batteries. Widodo et al.[26] compared the SVM and RVM for battery RUL prediction with a new health indicator. Pattipati et al.[11] proposed a BMS that estimates three critical characteristics of the battery (SOC, SOH, and RUL) with a data-driven approach. Based on an equivalent circuit model consisting of resistors, capacitor, and Warburg impedance, the capacity fade and power fade is predicted with SVM algorithm, which characterize the SOH as well as estimate the SOC of the battery. Later, Pattipati et al.[37] applied the hidden Markov model (HMM) model into the SVM to realize the prognostic uncertainty representation. Nuhic et al.[38] applied the SVM algorithm combined training and testing data processing based on fisher ratio to accurately estimate the SOH and RUL of li-ion batteries, decreased the influence of environmental and load conditions

Although the SVM algorithm has been widely used in the field of prediction and gradually extended to the RUL estimation of lithium-ion batteries, there are still some deficiencies needed to be improved, including that the kernel function must satisfy Mercer conditions, and the number of support vectors are sensitive to boundary errors, the parameters selection lack of guidance and hard to determined, and the predicted results lack of uncertainty ability.

4) RVM

Similar to SVM, the RVM almost has the same function for prediction. But the RVM is based on Bayesian framework and support the uncertainty representation and management for the predicted output. Moreover, the RVM is of high sparsity, as a result, it can effectively avoid the "over-fit" or "less-fit"[39]. The regression model of RVM is as,

$$P(t_n|x_n, w, \sigma^2) = N(y(x_n; w), \sigma^2) \tag{4}$$

where t_n is the regression output which obeys normal distribution with mean y and variance σ^2, X is the input and W is the regressive coefficients.

Saha et al.[40] built the RVM regression model with battery internal parameters, to track the degradation process. Furthermore, the PF algorithm is applied to obtain adaptive parameters for RVM model. Saha et al.[30] compared different data-driven methods for lithium-ion batteries, including Autoregressive Integrated Moving Average (ARIMA) model, RVM algorithm, and other model-based methods, especially the prognostic uncertainty is emphasized and evaluated.

Note that the long-term prediction capability of RVM algorithm is poor, so it is difficult to obtain satisfied RUL estimated result by using RVM directly[41]. Wang et al.[42] integrated RVM algorithm and conditional three-parameter capacity degradation model to predict the future health conditions of lithium-ion batteries. The RVM algorithm is utilized to derive the relevance vectors (RVs), and the conditional three-parameter capacity degradation model is developed to track the predictive values at the cycles of the RVs. The RUL of lithium-ion batteries is estimated by extrapolation of the conditional three-parameter capacity degradation model to the failure threshold. Zhou et al.[43] proposed a combined RVM algorithm to achieve RUL prediction, in which the Grey Model (GM) is involved to improve the poor prediction ability of the RVM algorithm.

5) GPR

As a nonparametric model, the GPR can achieve prognostic uncertainty representation. The GPR can model any linear and nonlinear system behavior to predict system future status. Moreover, prior knowledge can be combined to conduct prediction in Bayesian framework.

Saha et al.[17] use the correlation of impedance $R_E + R_{CT}$ (here R_E the electrolyte resistance is, and R_{CT} is the charge transfer resistance) and remaining capacity to achieve prediction based on GPR model. The remaining capacity and RUL is indirectly estimated based on the predicted $R_E + R_{CT}$, in which the mean and variance of RUL value are output. Liu et al.[44] simulated the battery degradation behavior with the exponential squared covariance function and periodic squared covariance function, the residual life prediction of lithium-ion battery is achieved with the hyper-parameters adjustment based on GPR model. The most of disadvantages for GPR model is that the adjustment of hyper-parameters is difficult and complicated, also with high computation complexity.

We compare several different data-driven prognostic methods for lithium-ion battery RUL estimation, which is shown as Table 1.

Table 1 Comparison of different data-driven RUL prediction methods

Index	Methods	Advantages	Disadvantages
1	AR model	Simple computing	Low prediction precision, point estimator
2	ANN	Available improved ANN algorithms are numerous, satisfied precision	Lack of uncertainty capability, complex training and over-fitting
3	SVM	Small sample size, high precision, and convergence	Lack of uncertainty capability, parameters identification is challenging
5	GPR	Uncertainty representation	Complicated hyper-parameters, high computation
5	RVM	Not many parameters, high sparsity, uncertainty management	Poor long-term prediction capability and low stability

There are so many other types of data-driven prognostic approach for lithium-ion battery RUL prediction, such as Grey Model (GM), exponential regression model, Markov chains, similarity matching, etc., we will not cover all of the other methods in this paper.

The data-driven approach only considers the features of data and establishes the prediction model with only the historical and monitoring data, in which the physical process and mechanism is not involved. The adaptability and robustness of data-driven method is always a challenge for the applications of these methods. In some situation, the sensitivity of parameters setting is another major concern for the applications.

Among various data-driven prognostic approaches, the methods supporting uncertainty representation and management are the hot issues for battery applications. Especially, for the uncertainty theory and evaluation, there are still lots of efforts should be taken.

4.2 Hybrid approaches

To improve the unsatisfied performance of single data-driven method for lithium-ion battery RUL estimation, lots of fusion and integrated algorithms are proposed, which become the mainstream in this area.

In general, due to the complexity of life prediction, especially the nonlinearity, non-stationary, and non-convergence in degradation process, it leads poor performance for single data-driven algorithm[45].

There are two categories of fusion approaches: one is the fusion method combining model-based approach and data-driven approach, the other is the hybrid approach integrated different data-driven methods to overcome the drawback of the single algorithm. In this paper, we will only focus on the latter situation.

Liu et al.[27] proposed an improved Echo State Networks (ESNs) algorithm for battery RUL estimation. The prior monotonic restriction is brought to basic ESNs, that makes the prediction feature mapping the degradation trend. Moreover, the Ensemble Learning (EL) algorithm is used to integrated a series of sub-models to improve the predicting stability. Kozlowski[21] presented a data-driven battery RUL prediction approach combined three predictors−ARMA model, neural networks and fuzzy to achieve a fusion prognostic method. Saha et al.[46] introduced a battery RUL estimation method that combined RVM and PF algorithm (the PF algorithm realizes the parameters identification of the RVM model). Xing et al.[47] developed an ensemble model, which merges fused regression model and PF algorithm, for predicting the RUL of the lithium-ion battery (the PF algorithm adjusts the parameters of the fused regression model on-line to track the degradation trend of the battery cycle life). Hu et al.[48] provided an ensemble data-driven method that integrates multiple member algorithms using a weighted sum model (three weighting schemes are applied and optimized by the k-fold cross validation). Among these fusion prognostic strategies, Liu et al.[49] presented a fusion framework, data-driven prognostic method and model-based PF approach are integrated, to increase the system's long-term prediction performance.

In the future, the ensemble learning can be widely used for the fusion and integration of different data-driven prognostic methods. The on-line algorithms and uncertainty fusion should be the key issues in the hybrid approaches for battery RUL estimation.

5 Challenge and future perspective

Currently, in the field of lithium-ion batteries, the development of new battery materials, new manufacturing technologies, especially high safety, high energy density batteries are the hotspots. And the related issues including condition monitoring, state estimation and prediction, health management, are still meeting a lot of challenges and should be studied further.

The future trends for the lithium-ion battery monitoring, prognostics and RUL estimation should be focused on are as follows.

1) Monitoring methods and technologies: the on-line condition monitoring including state-aware technology, health state parameters identification and extraction need to be further studied.

2) Smart and embedded sensing and sensor technologies for lithium-ion battery.

3) A integrated prognostic framework involving state monitoring, anomaly detection, intelligent diagnostics and prognostics can be considered.

4) The degradation modeling and remaining useful life estimation under dynamic operating condition.

5) Fusion and integrated methods for lithium-ion battery health status assessment.

6) Accelerated degradation test and accelerated life test for lithium-ion batteries considering on-line and off-line conditions.

7) Related issues on battery pack should be paid more attentions, and only the prognostics and RUL prediction for single battery can not provide enough decision-making reference in actual industrial applications.

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Authors' Biographies

LIU Datong, born in 1982, is currently an assistant professor in the Department of Automatic Test and Control, School of Electrical Engineering and Automation, Harbin Institute of Technology (HIT), China. He obtained his Ph. D degree from HIT in 2010. His research interests include automatic test technologies, intelligent test data processing, and prognostics and health management, etc.
Tel: +86-451-86413533ext.514;
E-mail: liudatong@hit.edu.cn

ZHOU Jianbao, born in 1980, is currently a postdoctoral fellow in the School of Electrical Engineering and Automation, Harbin Institute of Technology (HIT), China. He obtained his Ph. D degree from HIT in 2013. His major interests include automatic test technologies, battery management system, and embedded computing technology for test data processing, etc.
E-mail: zhoujianbao@163.com

PENG Yu, born in 1973, is a professor in the Department of Automatic Test and Control, School of Electrical Engineering and Automation, Harbin Institute of Technology, China. He is also the Associated Dean of School of Electrical Engineering and Automation. His research areas include virtual instruments and automatic test technologies, prognostics and system health management, and reconfigurable computing, etc.
E-mail: pengyu@hit.edu.cn