Int. J. Electrochem. Sci., 15 **(2020)** 8674 – 8693, doi: 10.20964/2020.09.30

International Journal of ELECTROCHEMICAL SCIENCE
www.electrochemsci.org

A Nonlinear Prediction Method of Lithium-Ion Battery Remaining Useful Life Considering Recovery Phenomenon

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Received: 4 April 2020 / *Accepted:* 3 June 2020 / *Published:* 10 August 2020

Remaining useful life (RUL) prediction is the core of prognostic and health management (PHM). Lithium-ion battery is an important power source in the new energy field. Predicting its RUL accurately has great significance to the development of new energy. Experiment shows, recovery phenomenon exists in the process of using lithium-ion battery and it will make a huge impact on the lithium-ion battery life. However, existing prediction method based on artificial intelligence can't get the probability distribution function (PDF), and the PDF can reflect the uncertainty characteristics of the RUL, and can't quantify the RUL prediction results. In view of this situation, based on statistical data-driven, this paper proposes a deterioration modeling and RUL prediction method that considers the effects of lithium-ion battery recovery phenomenon. Firstly, based on the definition of the first hitting time, a lithium-ion battery deterioration model considering the recovery effect is established. Then, considering the effect of recovery on the lithium-ion battery life, based on the lithium-ion battery deterioration model, the probability density functions of lithium-ion battery life and RUL under the influence of recovery are theoretically derived. Furthermore, the unknown parameters are estimated by maximum likelihood estimation method. Finally, using 18650 lithium-ion battery deterioration data and NASA public data set to prove the effectiveness of the method proposed in this paper.

Keywords: remaining useful life ; recovery phenomenon; lithium-ion batteries; deterioration modeling

1. INTRODUCTION

Due to the development of new energy and the continuous exploration of human beings in the new energy field, electric vehicles (EV) are widely used in the daily life [1-3]. As the power resource of EV, lithium-ion batteries are the core of electric vehicle power systems. During the use of lithium-ion batteries, their capability and health status will degenerate inevitably due to various operational factors [4]. During operation, some devices will undergo performance deterioration and eventually evolve into failure due to the combined effects of internal stress and the external environment. Such devices are generally referred to as random deterioration devices [5-9]. In practical applications, in the event of an accident resulting in the failure of a lithium-ion battery, the resulting property damage or even environmental damage is often immeasurable. For example, in April 2019, a Tesla Model S burned in Shanghai, China, directly causing the three nearby vehicles to burn together, causing a large amount of property damage. Therefore, for such random deterioration device, if it can be in the early stage of its performance deterioration , especially when it has not caused any major hazard, according to the detecting information, people can timely discover the abnormality or quantitatively evaluate the health status of the device and predict the RUL of the device. According to RUL, it is important to determine the optimal timing for device maintenance, which has great significance for ensuring the operational safety, reliability and economy of the device.

In recent years, with the continuous improvement of the reliability and safety requirements of key device, accurately estimating and predicting the probability of device failure in the future has become a hot issue for scholars all over the world [5, 7-9]. Engineering practice shows that PHM technology can reduce maintenance support costs, which is especially important in areas with high safety and reliability requirements such as new energy [10,11]. The core problem of PHM is the data obtained through state monitoring, predicting the RUL of the device, and determining the optimal maintenance timing of the device based on this information to achieve the lowest economic cost or the minimum device aging risk, and finally achieve state-based predictive maintenance and autonomous guarantee [12]. In this problem, predicting the RUL of the device through the state monitoring data of the device is the key to achieving health management. Scholars from various countries have given extensive attention to the study of RUL predictions and have made considerable progress in the past decade. In the literature [13] on PHM, Pecht proposed that the existing RUL prediction methods are divided into three categories: mechanism-based methods, data-driven methods, and fusion methods. Literature [14] proposed a fusion forecast method, which combines data-driven methods and fault physics methods to forecast the RUL of electronic device. This approach integrates advantages and overcomes the limitations of data-driven methods and fault physics methods, providing more accurate predictions. Literature [15] summarized the current research on data-driven methods. By analyzing the problems existing in the practical application of the on-board lithium-ion battery, the issues that need to be resolved in the future are determined. The existing research in literature [17] for most online RUL prediction was limited to the linear deterioration model. Under the framework of generalized nonlinear deterioration models with stochastic and deterministic parameters, a new RUL forecast method is proposed. Literature [18] described an enhanced particle filter (PF) method for predicting the lithium-ion battery RUL. Based on the enhanced PF, an online rolling bearing RUL prediction framework is designed, and a dynamic model of PF is constructed through a multi-stage autoregressive model. In literature [19], this paper develops a convex quadratic formula that combines the information in the degeneracy curve of the historical unit with the field sensing data of the operating unit to estimate the fault threshold of the specific unit at the site. By estimating the fault threshold of the operating unit more accurately in real time, the RUL can be predicted more accurately. Literature [20] proposed a comprehensive prediction method to unify the time intervals of two health indicators (HI) types, battery equal discharge voltage and capacity difference series, and conduct direct and indirect RUL prediction for lithium-ion batteries. Literature [21] proposed a lithium-ion battery RUL forecast method by using ELM algorithm combined with improved PSO algorithm. Literature [22] used the heuristic Kalman algorithm (HKA) to optimize the input weights and biases of the ELM algorithm. The mean square error (MSE) obtained from the ELM is used as the cost function of the HKA algorithm, and the optimized particles in the HKA are used as the weights and biases of the ELM predictor. Literature [23] proposed a RUL forecast method based on random survival forest (RSF) to predict the reliability of lithium-ion battery.

The lithium-ion battery data used in the experiments in the current literature are mostly obtained under continuous discharge. However, in daily life, lithium-ion batteries are non-continuous discharging. As using lithium-ion batteries, when the battery is in a pause state, the capacity recovery occurs. The lithium-ion battery recovery phenomenon can affect the life of lithium-ion batteries. Therefore, considering the lithium-ion battery recovery phenomenon for deterioration modeling, and further predicting lithium-ion battery RUL is an urgent problem to be solved. Literature [24] introduced a stochastic model of battery, which simulates the charge recovery phenomenon caused by lithium-ion battery discharge, and points out that the amount of charge recovered depends on the battery charge stage and the duration of the state of rest during discharge. Literature [25] highlighted the performance recovery phenomenon in the deterioration process of high-power lithium-ion batteries used in electric vehicles. However, neither the literature [24] nor the literature [25] deal with the prediction of the lithium-ion battery RUL. Literature [26] proposed a new lithium-ion battery RUL forecast method by combining wavelet decomposition technique (WDT) and nonlinear autoregressive neural network (NARNN) model. However, this method can't obtain the PDF and the PDF reflects the RUL uncertainty characteristics, and can't quantify the uncertainty of the RUL forecast results. Therefore, this paper chooses to use the statistical data-driven method to forecast the lithium-ion battery RUL.

The deterioration process of lithium-ion battery is a dynamic, complex and nonlinear electrochemical process [27]. When a lithium-ion battery is used, the capacity and RUL of the battery exhibit an irreversible tendency to gradually decrease over time. In addition, the lithium-ion battery capacity deterioration is accelerated in the late battery life, exhibiting nonlinear characteristics. Therefore, considering the influence of recovery phenomenon of lithium-ion battery and the lithium-ion battery deterioration nonlinear characteristics, a new lithium-ion battery RUL forecast method is proposed. The main contributions of this paper are as follows:

(1) Based on the concept of FHT, considering the influence of recovery in modeling and adding the amount of recovery in the deterioration model, a nonlinear lithium-ion battery deterioration model considering the effect of recovery is proposed.
(2) According to the lithium-ion battery deterioration model, the probability density functions of lithium-ion battery life and RUL considering recovery effect is derived.
(3) The lithium-ion battery deterioration experiment considering the recovery effect was designed, and the 18650 lithium-ion battery deterioration data required in the experimental part of this paper was obtained.

2. MODELING CONSIDERING RECOVERY PHENOMENON

Based on the lithium-ion battery deterioration raw data, the lithium-ion battery RUL forecast problem under the influence of recovery phenomenon can be described by Fig 1. Where the abscissa is the number of cycles, and the ordinate is the amount of the lithium-ion battery deterioration $\{X(t), t \geq 0\}$ as the cycle number increases. ω is the failure threshold of the lithium battery and is generally determined by industry standards, reliability and accuracy requirements of the product. The value of ω is generally 20%~30%. The curve in the Fig.1 is the lithium-ion battery deterioration path under the influence of recovery. T is the failure time of the lithium-ion battery under the effect of recovery, that is, the life of the lithium-ion battery under the influence of recovery. The curve in the box is an enlarged view of the recovery process of the lithium-ion battery during the pause stage.

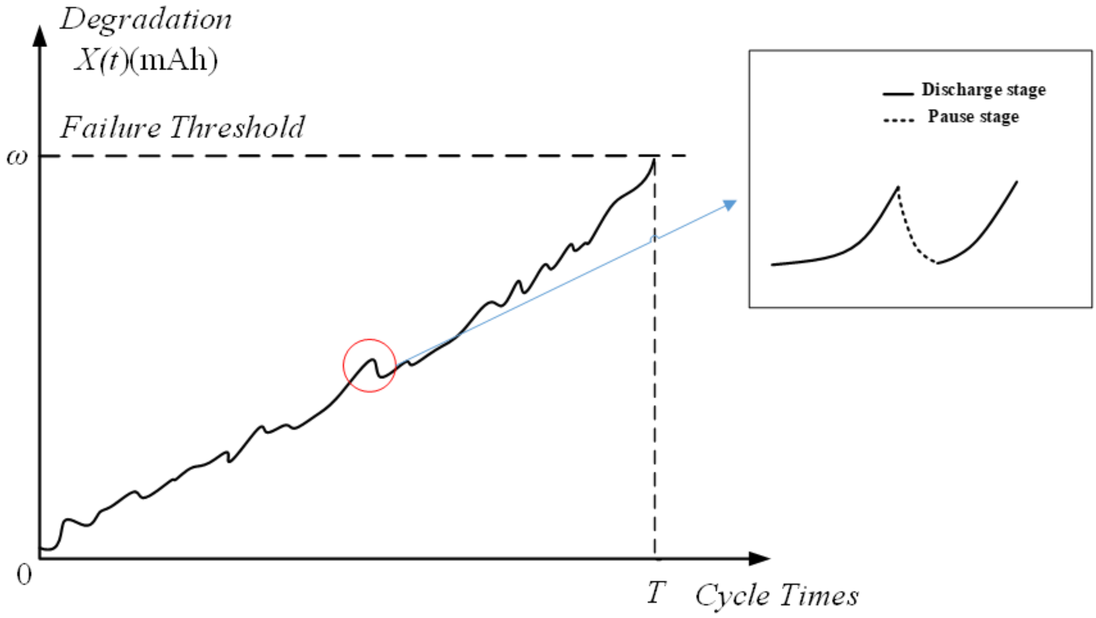


Figure 1. Lithium-ion battery deterioration diagram considering recovery

First hitting time, that is, the time required for the equipment deterioration to reach the failure threshold for the first time. Based on the concept of the FHT of the stochastic process [28], the life of the degraded device life T and the RUL L_k at time t_k are defined. The life T and the RUL L_k at time t_k can be expressed as

$$T = inf\{t : X(t) \geq \omega \mid X(0) < \omega\} \tag{1}$$

$$L_k = inf\{l_k : X(l_k + t_k) \geq \omega \mid X(t_k) < \omega\} \tag{2}$$

Where $X(0)$ is the initial state of the lithium-ion battery, $X(t_k)$ is the amount of the lithium-ion battery deterioration at time t_k, and ω is a pre-set threshold.

2.1 Modeling of lithium-ion battery deterioration process without considering recovery phenomenon

The lithium-ion battery deterioration process is a nonlinear incremental process, which uses random process $\{X(t), t \geq 0\}$ to characterize the lithium-ion battery deterioration process. If the effect of the recovery process is not considered, through a deterioration process in which the deterioration path increases with time, the deterioration model of lithium-ion batteries at time t is:

$$X(t) = X(0) + \int_0^t \mu(\tau;\theta_\mu)\mathrm{d}\tau + \sigma B(t) \tag{3}$$

Where $\mu(\tau;\theta_\mu)$ is the nonlinear drift coefficient, if $\mu(\tau;\theta_\mu)$ is a constant, then $X(t)$ is linear deterioration process. σ is the diffusion coefficient. $B(t)$ is the standard Brownian motion, and $\sigma B(t) \sim N(0,\sigma^2)$, used to characterize the random dynamics of the deterioration process [29].

2.2 Modeling of lithium-ion battery deterioration process considering recovery phenomenon

Considering the effect of the recovery process and using random process $\{Y(t), t \geq 0\}$ to characterize the lithium-ion battery deterioration process. Through a deterioration process in which the deterioration path increases with time, the lithium-ion battery deterioration model at time t is:

$$Y(t) = X(t) + Z \tag{4}$$

Where $Y(t)$ is the total deterioration amount at the time t, Z is the total amount of recovery in the lithium-ion battery life cycle, and $Z \sim N(\mu_1, \sigma_1^2)$.

3. RUL PREDICTION OF LITHIUM-ION BATTERY

Based on the FHT concept, the PDF of deterioration device life T and the RUL at the t_k time L_k are $f_T(t)$ and $f_{L_k}(l_k)$. To solve the analytical expressions of $f_T(t)$ and $f_{L_k}(l_k)$, the following assumptions are given:

Assumption 1. Based on equation (1), if the detecting device is operating normally at time t, the device does not have a failure event before time t.

Assumption 2. If the potential deterioration process $\{X(t), t \geq 0\}$ reaches the failure threshold at t time, the probability of $\{X(t), t \geq 0\}$ exceeds the failure threshold ω before t time is negligible.

Based on Assumption 1 and Assumption 2, the conclusions are as follows:

Theorem 1. [30] For the deterioration process described by equation (3), if $\mu(\tau;\theta_\mu)$ is a continuous function of time t at $[0,\infty)$, based on Assumption 1 and Assumption 2, under the condition of given random parameters, the PDF of $\{X(t), t \geq 0\}$ exceeds failure threshold ω can be expressed as:

$$f_T(t) \cong \frac{1}{\sqrt{2\pi t}}\left[\frac{S_B(t)}{t} + \frac{1}{\sigma}\mu(t;\theta_\mu)\right] exp\left[-\frac{S^2{}_B(t)}{2t}\right] \tag{5}$$

Where $S_B(t) = \frac{1}{\sigma}\left[\omega - \int_0^t \mu(\tau;\theta_\mu)\mathrm{d}\tau\right]$.

3.1 RUL prediction of lithium-ion battery without considering recovery phenomenon

The key to finding the lithium-ion battery life T and the RUL L_k at time t_k is to derive the probability density function of T and L_k. Without considering the effect of lithium-ion battery recovery, according to Assumption 1, Assumption 2 and Theorem 1, the probability density functions of the lithium-ion battery life T and the RUL L_k at time t_k are:

$$f_T(t)=\frac{\omega-X(0)-\int_0^t\mu(\tau;\theta_\mu)\mathrm{d}\tau+\mu(\mathrm{t};\theta_\mu)\mathrm{t}}{\sqrt{2\pi\sigma^2t^3}}\times t_k \\ exp\left\{-\frac{\left[\omega-X(0)-\int_0^t\mu(\tau;\theta_\mu)\mathrm{d}\tau\right]^2}{2\sigma^2t}\right\} \tag{6}$$

$$f_{L_k}(l_k)=\frac{\omega-\mathrm{X}(t_k)-\int_{t_k}^{t_k+l_k}\mu(\tau;\theta_\mu)\mathrm{d}\tau+\mu(t_k+l_k;\theta_\mu)l_k}{\sqrt{2\pi\sigma^2{l_k}^3}}\times \\ exp\left\{-\frac{\left[\omega-\mathrm{X}(t_k)-\int_{t_k}^{t_k+l_k}\mu(\tau;\theta_\mu)\mathrm{d}\tau\right]^2}{2\sigma^2l_k}\right\} \tag{7}$$

3.2 RUL prediction of lithium-ion battery considering recovery phenomenon

Considering the effect of lithium-ion battery recovery, according to Assumption 1, Assumption 2 and Theorem 1, the probability density functions of the lithium-ion battery life T and the RUL L_k at time t_k are:

$$f_T(t)=\frac{\omega-X(0)-\int_0^t\mu(\tau;\theta_\mu)\mathrm{d}\tau+\mu(\mathrm{t};\theta_\mu)\mathrm{t}-\mu_1}{\sqrt{2\pi\left(\sigma_1^2+\sigma^2t\right)^3}}\times \\ exp\left\{-\frac{\left[\omega-X(0)-\int_0^t\mu(\tau;\theta_\mu)\mathrm{d}\tau-\mu_1\right]^2}{2\left(\sigma_1^2+\sigma^2t\right)}\right\} \tag{8}$$

$$f_{L_k}\left(l_k\right)=\frac{\omega-\mathrm{X}\left(t_k\right)-\int_{t_k}^{t_k+l_k}\mu\left(\tau;\theta_\mu\right)\mathrm{d}\tau+\mu\left(t_k+l_k;\theta_\mu\right)l_k-\mu_1}{\sqrt{2\pi\left(\sigma_1^2+\sigma^2 l_k\right)^3}}\times exp\left\{-\frac{\left[\omega-\mathrm{X}\left(t_k\right)-\int_{t_k}^{t_k+l_k}\mu\left(\tau;\theta_\mu\right)\mathrm{d}\tau-\mu_1\right]^2}{2\left(\sigma_1^2+\sigma^2 l_k\right)}\right\} \tag{9}$$

4. PARAMETER ESTIMATION

In order to complete the estimation of the unknown parameters $\theta_\mu,\mu_1,\sigma_1,\sigma$ in the Equation (3) and Equation (4), it is assumed that there are N devices under test, and the sampling time point of the n th device under test is $t_1^n,\cdots,t_m^n$, where m represents the measured value of the n th device, and $n=1,\cdots,N$. Therefore, based on the no recovery effect model the deterioration path of the k th sample point t_k^n of the n th device can be written as follows:

$$Y^n\left(t_k\right)=X^n\left(0\right)+\int_0^{t_k}\mu^n\left(\tau;\theta_\mu\right)\mathrm{d}\tau+\sigma B\left(t_k\right)+Z \tag{10}$$

Where $k=1,\cdots,m$. Quote the intermediate variable $R^n(t_k^n)=X^n\left(t_k^n\right)-X^n\left(0\right)$, the specific implementation of $R^n(t_k^n)$ is $r^n(t_k^n)$, and the corresponding deterioration data is $\left\{R^n(t_k^n)\text{=}r^n(t_k^n),n=1,\cdots,N,k=1,\cdots,m\right\}$. So, the Equation (10) can be expressed as follows:

$$R^n\left(t_k^n\right)=\int_0^{t_k^n}\mu^n\left(\tau;\theta_\mu\right)\mathrm{d}\tau+\sigma B\left(t_k^n\right)+Z \tag{11}$$

Further, let $T^n=\left(t_k^n,\cdots,t_m^n\right)'$, $R^n=\left(r^n\left(t_k^n\right),\cdots,r^n\left(t_m^n\right)\right)'$, where $\left(\bullet\right)'$ represents the transpose of a vector, and R represents a collection of deterioration data at this stage, consisting of $R^n,n=1,\cdots,N$. According to the independent incremental properties of Equation (11) and the standard Brownian Motion (BM) process, it can be seen that R^n obeys the multidimensional normal distribution, and its covariance and mean are as follows:

$$\mu^n=\mu^n\left(\tau;\theta_\mu\right)\bullet T^n+\mu_1 \tag{12}$$

$$\Omega^n=\sigma^2 Q^n+\sigma_1{}^2 I_m \tag{13}$$

Where

$$Q^n=\begin{bmatrix} t_1^n & t_1^n & \cdots & t_1^n \\ t_1^n & t_2^n & \cdots & t_2^n \\ \vdots & \vdots & \vdots & \vdots \\ t_1^n & t_2^n & \cdots & t_m^n \end{bmatrix} \tag{14}$$

And I_m is m-order identity matrix.

Then, the log likelihood function of θ_u, σ, μ_1 and σ_1 corresponding to all test numbers R is as follows:

$$\ln L = -\frac{mN}{2}\ln(2\pi) - \frac{N}{2}\ln|\Omega^n| - \frac{1}{2}\sum_{n=1}^{N}\left(R^n - \mu^n\right)'\left(\Omega^n\right)^{-1}\left(R^n - \mu^n\right) \qquad (15)$$

Substituting the Equation (12), the Equation (13) and the Equation (14) into the Equation (15), by maximizing the Equation (15), the MATLAB multidimensional search method can be used to obtain θ_μ, σ, μ_1 and σ_1. The similar method of maximum likelihood estimation is detailed in the literature [31, 32].

5. EXPERIMENTAL VERIFICATION

In order to prove the the proposed method effective, this paper predicts the RUL of lithium-ion batteries by using the proposed method based on the 18650 lithium-ion battery deterioration experimental data and NASA public data.

5.1 BTS battery detection system description

The device for obtaining the 18650 lithium-ion battery data set used in this paper is the BTS battery detection system. The connection diagram of each part of the device is shown in Fig.2, and it consists of three parts. Part 1 is a host computer, which is to send commands to collect and store the acquired battery data collected by part 2 in real time. Part 2 is a lithium-ion battery detection device. Its role is to receive control commands from part 1 to control the charging and discharging of the channel. Moreover, it collects and transmits data such as current and voltage of the channel in real time. Part 3 are lithium-ion batteries, the lithium-ion battery used in the experiment is Panasonic 18650B lithium-ion battery, the specific parameters of the battery are shown in Table 1.

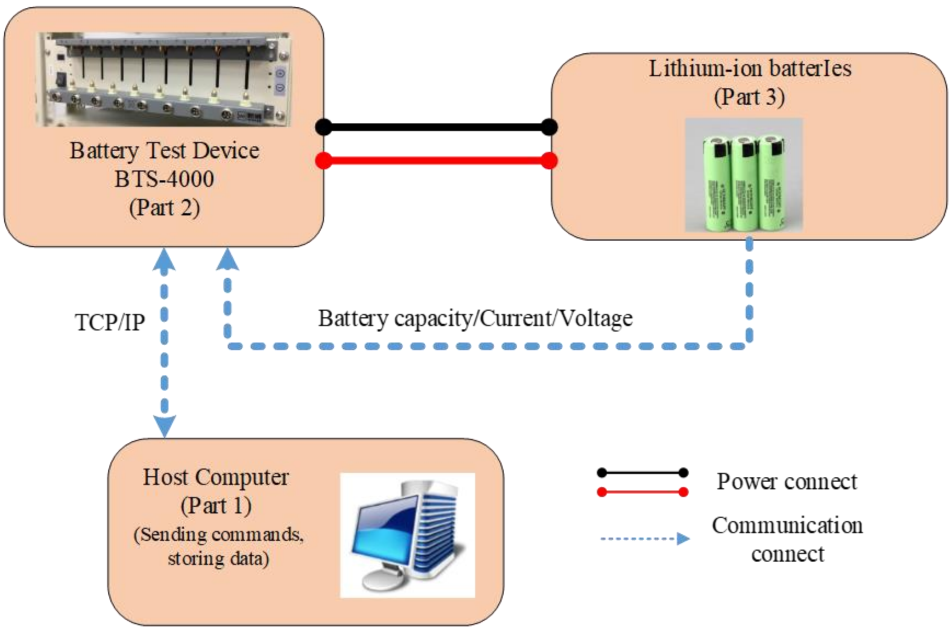


Figure 2. The diagram of BTS battery detection system

Table 1. Lithium-ion battery details

Items	Specification
Battery Type	NCR18650B
Capacity	3400 mAh
Nominal Voltage	3.6 V
Charging Voltage	4.2 V
Discharging End Voltage	2.5 V
Internal Resistance	Less than 100 mΩ
Size	Length 65 mm; Diameter 18 mm
Weight	Less than 48.5 g

5.2 Lithium-ion battery deterioration process description

In the use of lithium-ion batteries, there are roughly three states: charging state, discharging state and pausing state. When charging, the lithium-ion battery is first charging with constant current, and then charging with constant voltage. After the end of charging, the lithium-ion battery switches back and forth between the two states of discharging and pausing. The specific process used for lithium-ion battery can be found in literature [33]. As the lithium-ion battery deterioration cycle times number increases, the capacity of the lithium-ion battery gradually decreases. When the amount of the lithium-ion battery deterioration capacity reaches a preset failure threshold (20%~30%), it indicates that the lithium-ion battery has failed. If the lithium- ion battery does not meet the requirements for normal use, the lithium-ion battery life is considered to be over.

5.3 Acquisition of 18650 lithium-ion battery experimental data

The data set used in the experiments in this paper is the deterioration data of 18650 lithium-ion battery. The flow chart of the deterioration data acquisition of lithium-ion battery is shown in Fig.3. The specific test procedure can be found in literature [33]. The specific experiment parameters of the 18650 lithium-ion battery deterioration experiment are shown in Table 2.

Table 2. The specific experiment parameters

Items	Specification
Constant Current Charging Current	3.4 A (1 C)
Charging End Voltage	4.2 V
Constant Voltage Charging Voltage	4.2 V
Charging End Current	0.34 A (0.1 C)
Discharging Current	3.4 A (1 C)
Discharging End Voltage	2.5 V

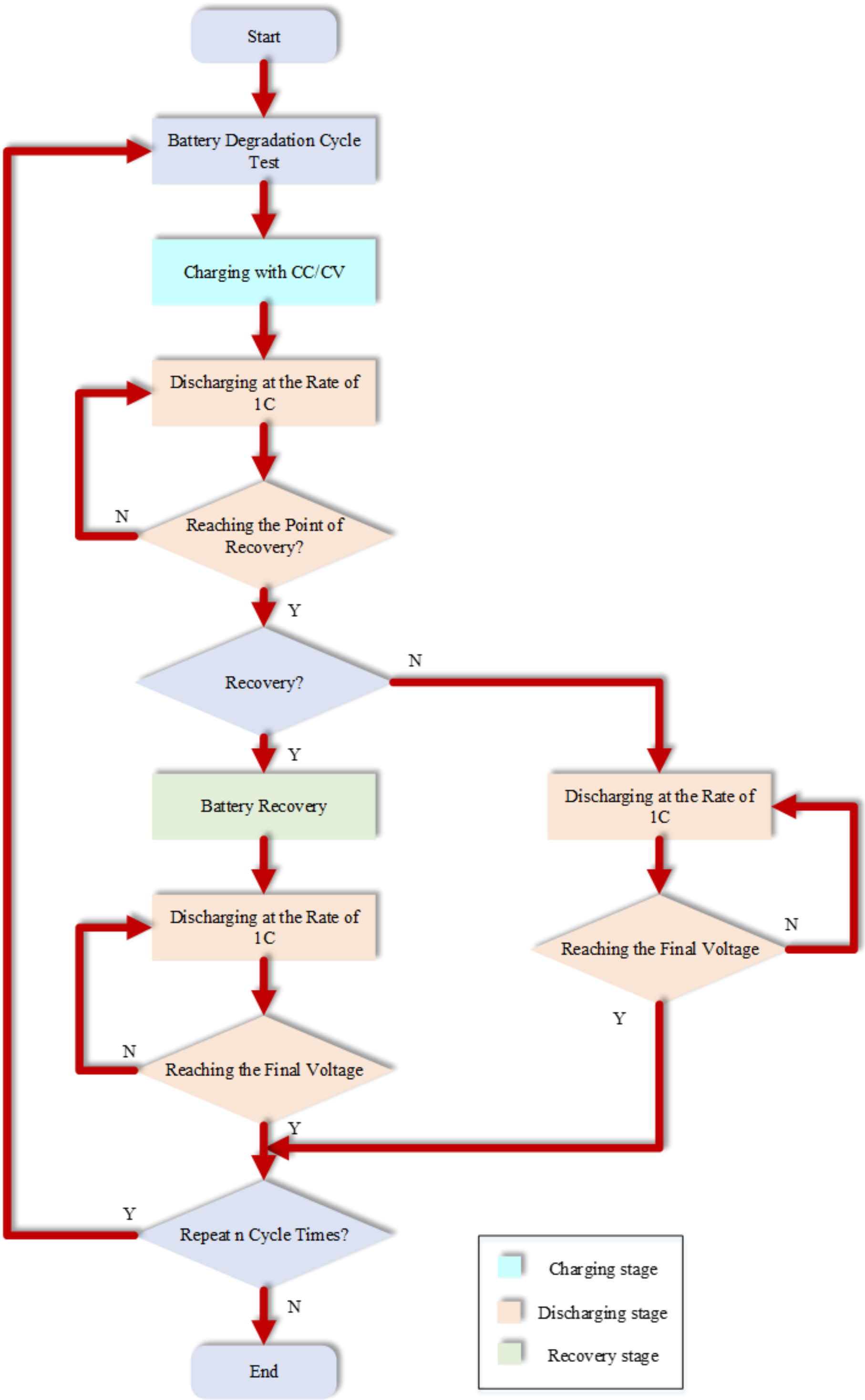


Figure 3. Flow chart of raw data acquisition of lithium-ion battery

5.4 18650 lithium-ion battery deterioration data

The lithium-ion battery deterioration data used in this experiment is the monitoring data of the same batch and same lithium-ion batteies at the same detection point. In the process of obtaining lithium-ion battery deterioration data, the test environment (temperature, humidity, etc.) and lithium-ion battery test time meet the test requirements, making the deterioration process relatively stable. The default failure threshold for lithium-ion battery deterioration is $\omega = 0.2$ (20%). When the lithium-ion battery capacity deterioration exceeds 20% of the rated capacity, it indicates that the lithium-ion battery has failed. In this paper, the first 200 data of two sets of deterioration data are used. Unit 1 is used to estimate parameters and Unit 2 is used for experimental verification. The specific deterioration path is shown in Fig.4.

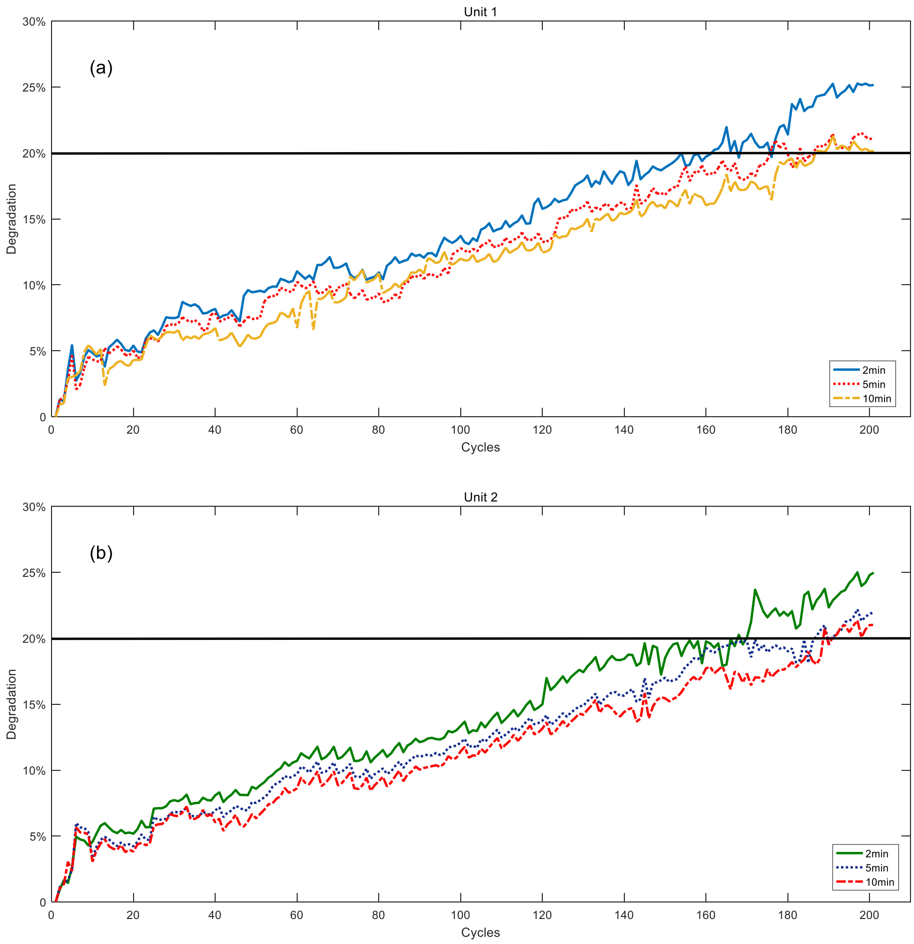


Figure 4. Deterioration path of lithium battery (a) Deterioration path is used to estimate parameters (b) Deterioration path is used for experimental verification

5.5 NASA public lithium-ion battery data

The method proposed in this paper is applied to the lithium-ion battery data published by NASA's Ames Research Center [34], and the capacity deterioration of lithium-ion batteries is analyzed to prove the proposed method effective. The B18, B5, and B7 batteries were selected from the public data as the verification of the model and algorithm. This data set shows that 25% of the original capacity loss will cause the lithium-ion battery to lose its ability to provide the required power supply, so the failure threshold is set to 0.25. The original deterioration data is shown in Fig.5.

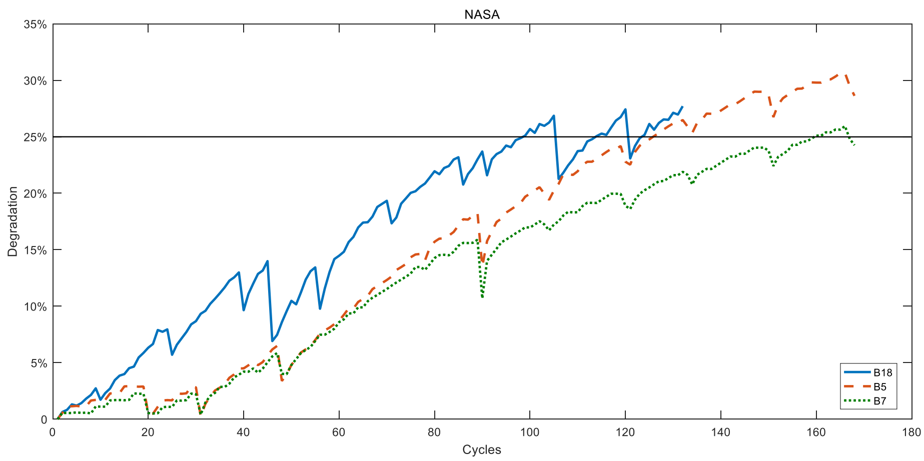
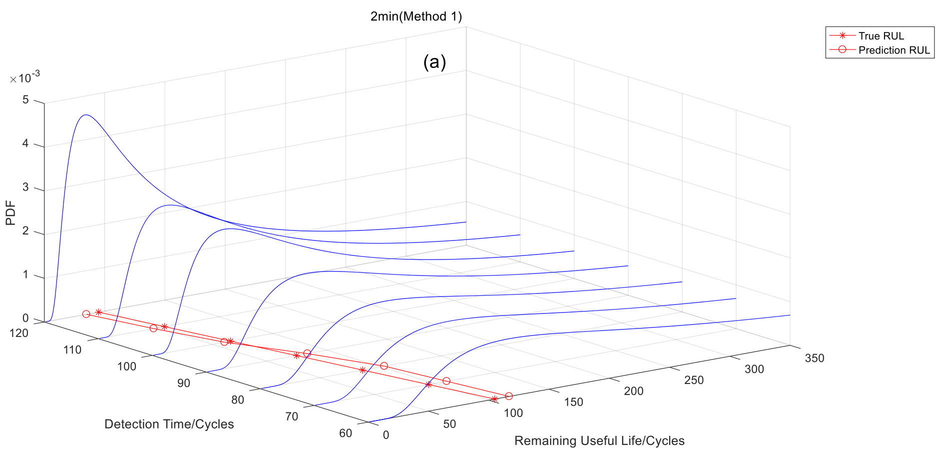
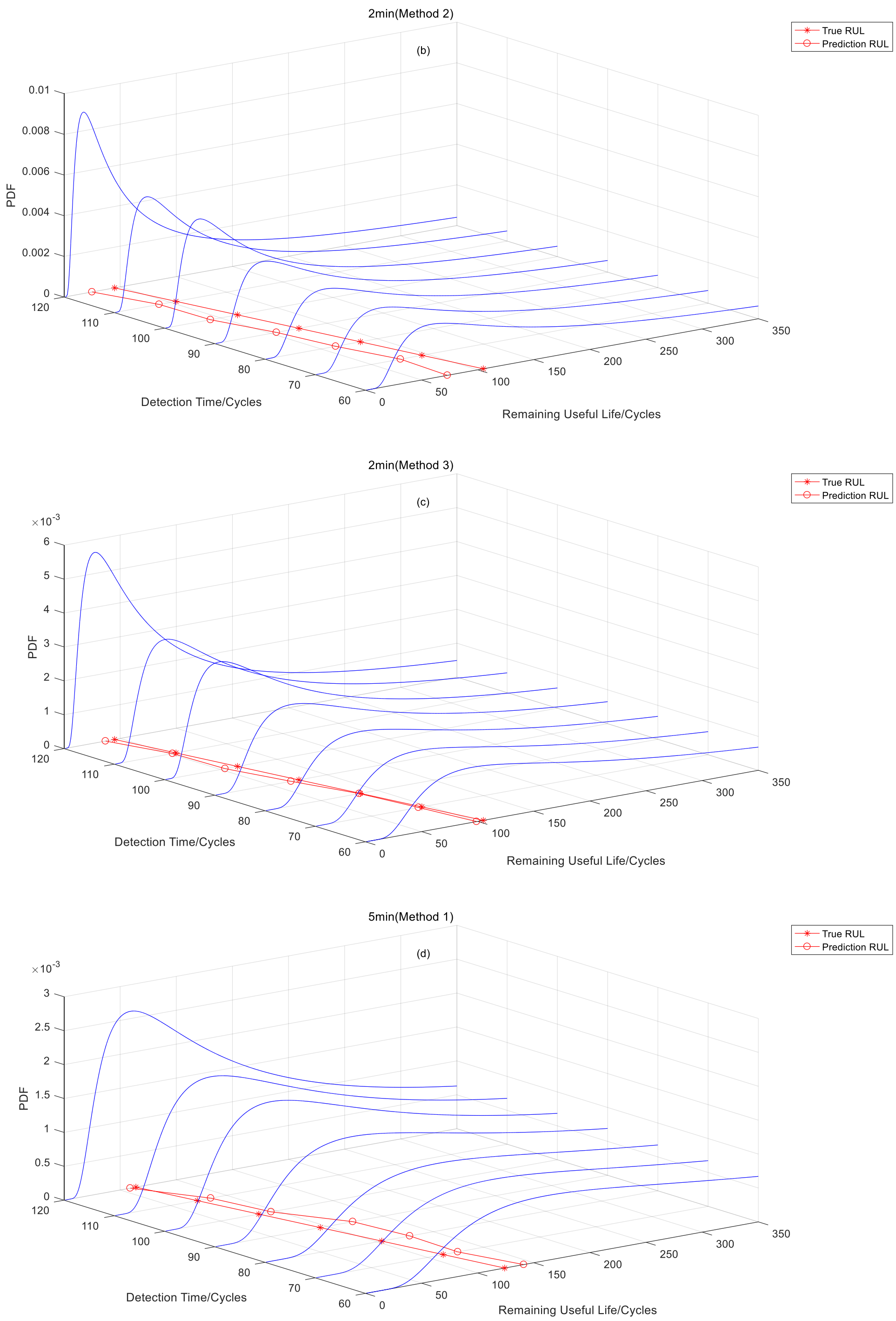


Figure 5. Deterioration path of lithium battery (NASA)

5.6 Lithium-ion battery RUL prediction based on 18650 lithium-ion battery data

As shown in Fig.4 (Unit 2), the lithium-ion batteries with recovery times of 2 min, 5 min, and 10 min exceeded the failure threshold after 165, 184, and 187 cycles. Therefore, it can be considered that the life of the lithium-ion batteries having recovery time of 2 min, 5 min, and 10 min are 165, 184, and 187 charge and discharge cycles. The method in [33] is defined as method 1, the method in [30] is defined as method 2, and the paper proposed method is defined as method 3. Three methods were used to forecast the lithium-ion battery RUL. The forecast results are shown in Table 3. From 60 cycles to 120 cycles, one detection time point is set every 10 cycles, and there are 7 detection time points. The life PDF and RUL prediction values for each detection time are shown in Fig.6. According to Fig 6, the experimental results can be compared more intuitively and the experimental methods can be analyzed.




2min(Method 2)
(b)
True RUL
Prediction RUL
PDF
Detection Time/Cycles
Remaining Useful Life/Cycles
2min(Method 3)
(c)
True RUL
Prediction RUL
PDF
Detection Time/Cycles
Remaining Useful Life/Cycles
5min(Method 1)
(d)
True RUL
Prediction RUL
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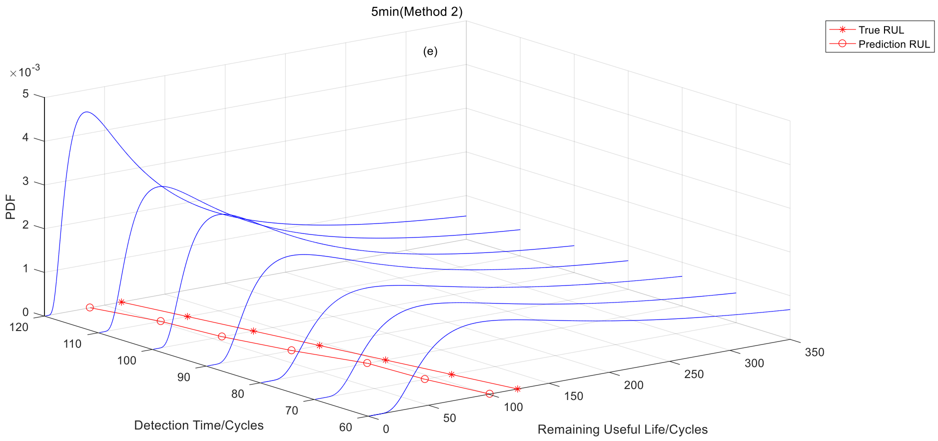
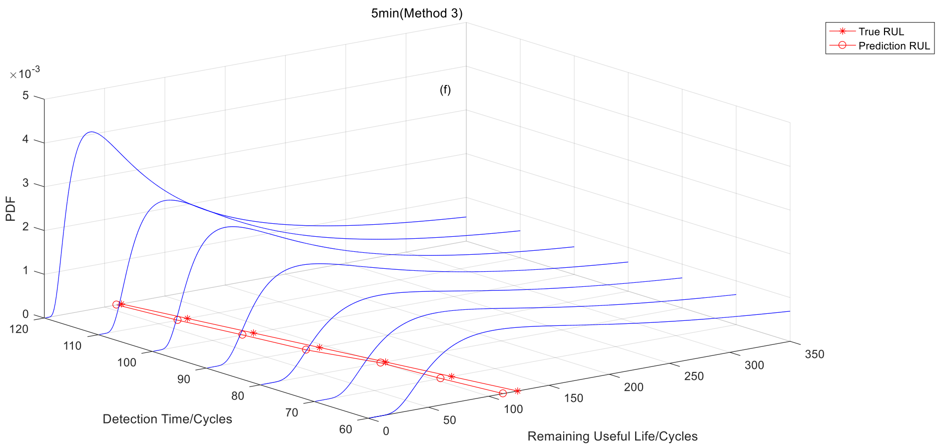
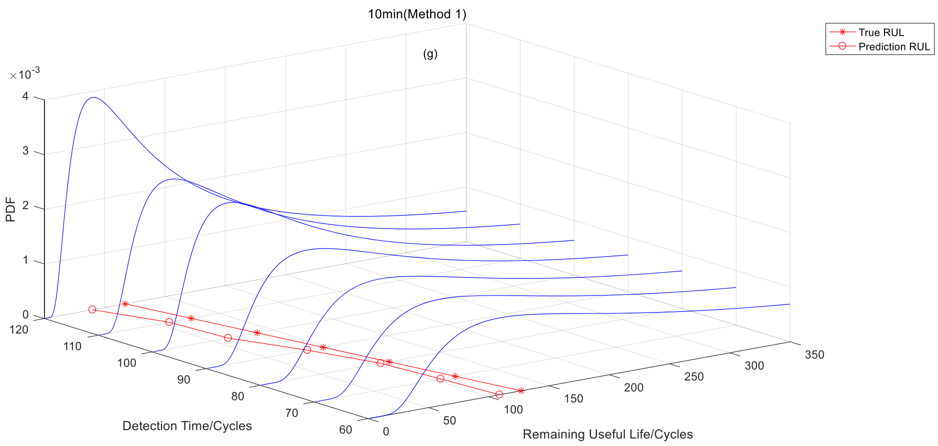
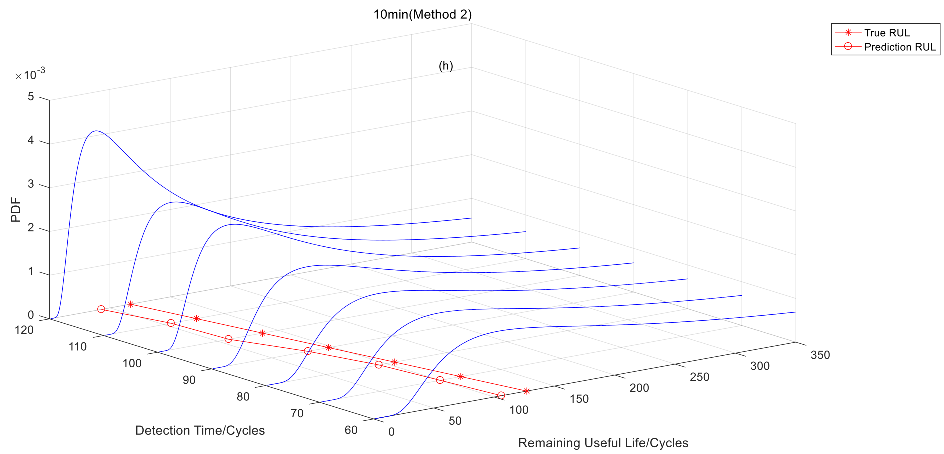
Detection Time/Cycles
Remaining Useful Life/Cycles


5min(Method 2)
(e)
True RUL
Prediction RUL
$\times 10^{-3}$
PDF
Detection Time/Cycles
Remaining Useful Life/Cycles


5min(Method 3)
(f)
True RUL
Prediction RUL
$\times 10^{-3}$
PDF
Detection Time/Cycles
Remaining Useful Life/Cycles


10min(Method 1)
(g)
True RUL
Prediction RUL
$\times 10^{-3}$
PDF
Detection Time/Cycles
Remaining Useful Life/Cycles



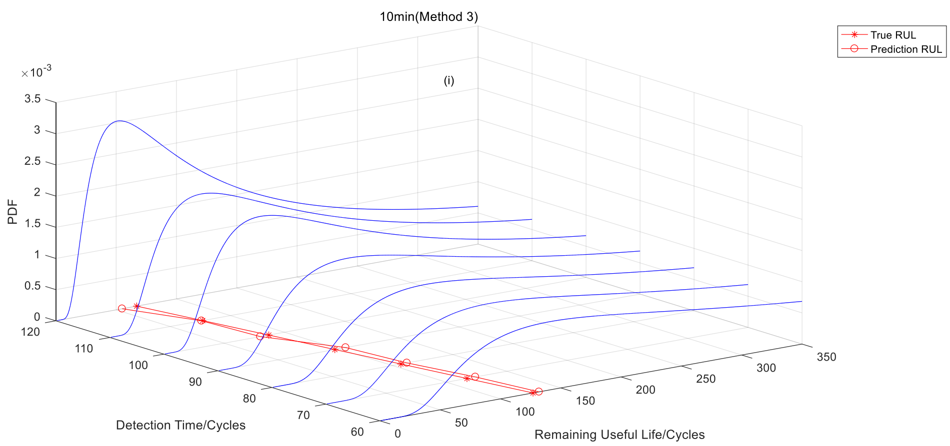


Figure 6. Comparison of RUL probability density estimation results by using three methods at each detection time based on three recovery time (a) Recovery time 2 min(method 1) (b) Recovery time 2 min(method 2) (c) Recovery time 2 min(method 3) (d) Recovery time 5 min(method 1) (e) Recovery time 5 min(method 2) (f) Recovery time 5 min(method 3) (g) Recovery time 10 min(method 1) (h) Recovery time 10 min(method 2) (i) Recovery time 10 min(method 3)

Table 3. Comparison of error between three prediction methods. (18650)

Method	**Recovery Time/min**	**Actual Life/ cycles**	**Predictive Life/ cycles**	**Absolute Error /cycles**	**Relative Error**
Method 1	2	165	177	12	7.27%
Method 2	2	165	144	21	12.7%
Method 3	2	165	162	3	1.82%
Method 1	5	184	199	15	8.15%
Method 2	5	184	166	18	9.78%
Method 3	5	184	175	9	4.81%

Method 1	10	187	161	26	13.9%
Method 2	10	187	167	20	10.7%
Method 3	10	187	191	4	2.14%

5.7 Lithium-ion battery RUL prediction based on NASA public data

It can be seen from the raw data shown in Fig 5 that the actual life of the three lithium-ion battery types of B18, B5 and B7 is 99 cycles, 126 cycles and 160 cycles. The method in literature [35] is defined as method 1, the method in literature [30] is defined as method 2, and the paper proposed method is defined as method 3. Three methods are used to forecast the lithium-ion battery RUL. The forecast results are shown in Table 4.

Table 4. Comparison of error between three prediction methods. (NASA)

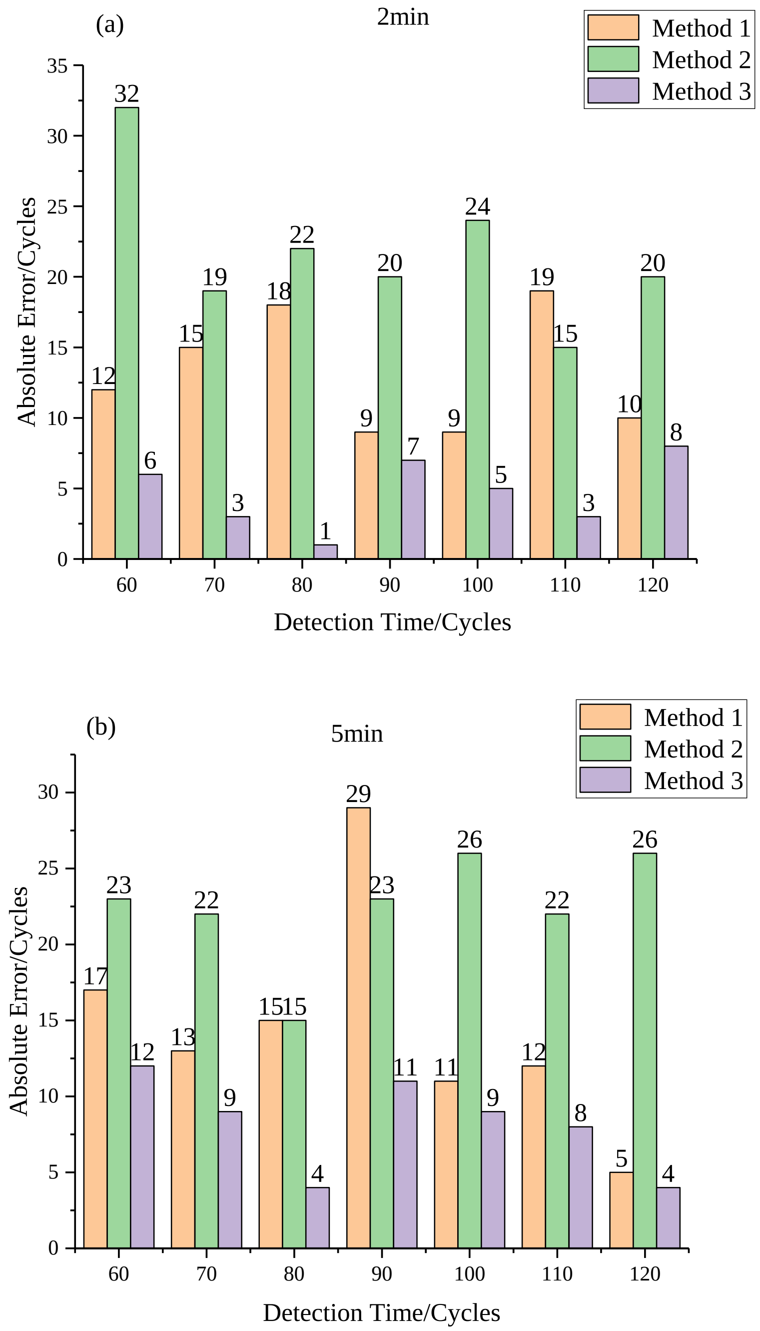
Method	**Battery Type**	**Actual Life/ cycles**	**Predictive Life/ cycles**	**Absolute Error /cycles**	**Relative Error**
Method 1	B18	99	86	13	13.13%
Method 2	B18	99	78	21	21.21%
Method 3	B18	99	105	6	6.06%
Method 1	B5	126	138	12	9.52%
Method 2	B5	126	140	14	11.11%
Method 3	B5	126	129	3	2.38%
Method 1	B7	160	164	4	2.50%
Method 2	B7	160	171	11	6.87%
Method 3	B7	160	162	2	1.25%

6. ERROR ANALYSIS

In order to analyze the experimental results better, the experimental error of the experiments based on two data sets was analyzed to prove the proposed method effective.

6.1 RUL Prediction Error Analysis Based on 18650 Lithium-ion Battery

Based on the 18650 lithium-ion battery deterioration data set, the RUL forecast error of the three methods at each detection time point is shown in Fig.7. The analysis error indicates that the error of using the method 1 and method 2 to forecast the lithium-ion battery RUL is bigger than the error of using the method 3 to forecast the lithium-ion battery RUL, indicating that the method 3 is more accurate for the RUL prediction.



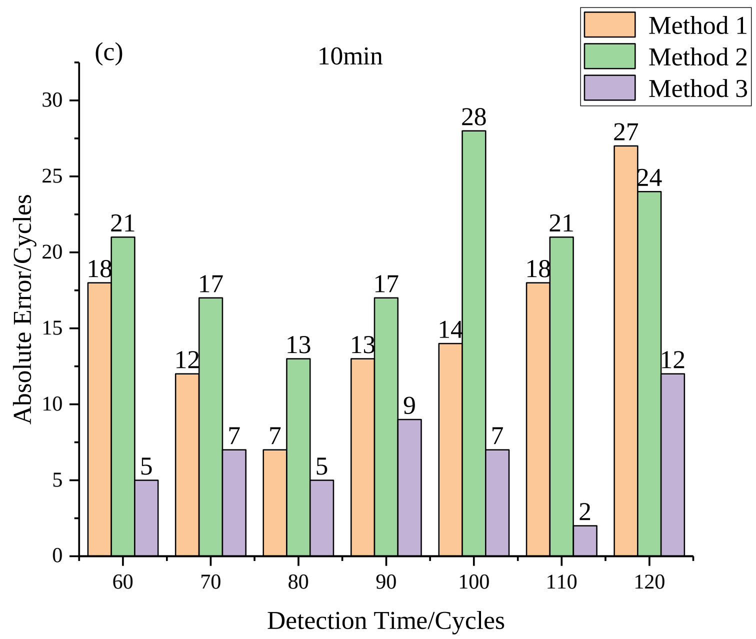


Figure 7. Comparison of errors by using three methods at each detection time based on three recovery time (a) Recovery time 2 min errors (b) Recovery time 5 min errors (c) Recovery time 10 min errors

6.2 RUL Prediction Error Analysis Based on NASA public data

Based on the NASA public data set, the life prediction errors for the three lithium-ion battery types using three methods are shown in Fig.8. The analysis error shows that the error of using method 1and method 2 is bigger than that of using method 3 to forecast the lithium-ion battery RUL, indicating that Method 3 is more accurate for RUL prediction.

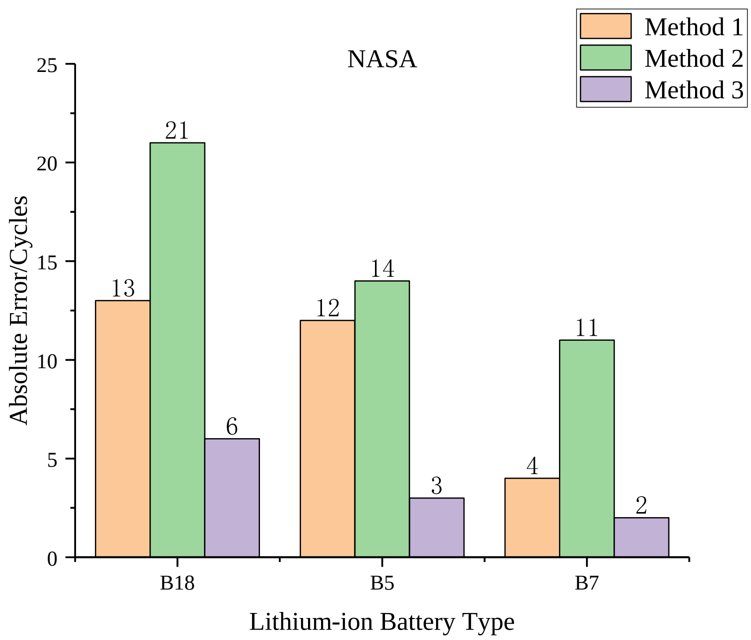


Figure 8. Comparison of errors by using three methods based on three lithium-ion battery types

7. CONCLUSION

In this paper, the recovery phenomenon in the lithium-ion battery deterioration process is studied. The modeling of nonlinear deterioration process and the prediction of lithium-ion battery RUL are studied. A deterioration model considering the lithium-ion battery recovery effect and the forecast method of RUL are proposed. In this paper, the recovery phenomenon in the process of lithium-ion battery is analyzed. The deterioration modeling and RUL prediction method considering recovery are proposed. The effectiveness of the proposed method is proved by comparing the experimental results of two data sets. The main conclusions are as follows:

(1) A nonlinear deterioration model is established, and the relevant RUL distribution is derived in the sense of FHT. It is found through analysis that if the drift coefficient is constant, it is a linear deterioration model, that is, the linear deterioration model and its first hitting time distribution are the model special cases used in this paper. Therefore, the model used in this paper is general.

(2) In order to realize the parameter estimation of the deterioration model in this paper, considering that the real deterioration process is affected by recovery, this paper introduces the recovery influence on the observation data in the deterioration modeling and proposes a parameter estimation method considering recovery influence.

(3) The lithium-ion battery RUL prediction this paper proposed method is applied to the 18650 lithium-ion battery deterioration data set and NASA public data set. The experimental results prove the proposed method effective.

In summary, this paper proposes a deterioration modeling and lithium-ion batteries RUL forecast method that consider recovery effects. Considering the effect of recovery, the deterioration experiment of lithium-ion battery was designed, and the deterioration data of lithium-ion battery considering the effect of recovery was obtained. The obtained data verified the proposed method effective. This paper can provide theoretical support for studying the lithium-ion battery recovery phenomenon in the field of electrochemistry, and help to study lithium-ion batteries better from the electrochemical direction, which has potential application value.

ACKNOWLEDGEMENTS
This work received financial support from the National Natural Science Foundation of China (No.61873175), the Key Project B Class of Beijing Natural Science Fund (KZ201710028028), and Academy for Multidisciplinary Studies of Capital Normal University, and the Beijing Youth Talent Support Program (CIT&TCD201804036). And the work supported by Capacity Building for Sci-Tech Innovation-Fundamental Scientific Research Funds (025185305000-187) and Youth Innovative Research Team of Capital Normal University.

References

1. J. Pereda and J. Dixon. *IEEE Transactions on Vehicular Technology*, 61(2012)1043.
2. S. G. Li, S. M. Sharkh and F. C. Walsh. *IEEE Transactions on Vehicular Technology*, 60(2011)3571.
3. R. Xiong, H. He and F. Sun. *Journal of Power Sources*, 229(2013)159.

4. F. Sun F, R. Xiong and H. He. *Applied Energy*, (2014), S0306261914012707.
5. X. S. Si, W. Wang, C. H. Hu and D. H. Zhou. *European Journal of Operational Research*, 213(2011)1.
6. L. Liao and F. Kottig. *IEEE Transactions on Reliability*, 63(2014)191.
7. A. K. S. Jardine and D. Lin, D. Banjevic. *Mechanical Systems and Signal Processing*, 20(2006)1483.
8. A. Heng, S. Zhang, A. C. C. Tan and J. Mathew. *Mechanical Systems and Signal Processing*, 23(2009) 724.
9. J. Z. Sikorska, M. Hodkiewicz and L. Ma. *Mechanical Systems & Signal Processing*, 25(2011) 1803.
10. N. M. Vichare and M. G. Pecht. *IEEE Transactions on Components and Packaging Technologies*, 29(2006) 222.
11. B. Sun, S. Zeng and R. Kang. *IEEE Transactions on Reliability*, 61(2012)323.
12. P. Yu. *Journal of Electronic Measurement and Instrument*, 24(2010)1007.
13. M. Pecht. *Encyclopedia of Structural Health Monitoring*. John Wiley & Sons, Ltd, 2009.
14. S. Cheng and M. Pecht. *IEEE International Conference on Automation Science & Engineering. IEEE*, 2009.
15. L. F. Wu, X. H. Fu and Y. Guan. *Applied Science*, 6(2016)1.
16. X. Li, X. Shu, J. Shen, R. Xiao, W. Yan and Z. Chen. Energies, 10(2017) 691.
17. Z. Q. Wang, C. H. Hu and H. D. Fan. *IEEE/ASME Transactions on Mechatronics*, (2017)1.
18. Y. Qian and R. Yan. *IEEE Transactions on Instrumentation and Measurement*, 64(2015)1.
19. A. Chehade, S. Bonk and K. Liu. *IEEE Transactions on Reliability*, 99(2017)1.
20. D. Liu, W. Xie and H. Liao and Y. Peng. *IEEE Transactions on Instrumentation and Measurement*, 64(2015)660.
21. J. Yang, Z. Peng, H. Wang, H. Yuan and L. Wu. International Journal of electrochemical Science, 13(2018)4991.
22. J. Yang, Z. Peng, Z. Pei, Y. Guan, H. Yuan and L. Wu. *International Journal of electrochemical Science*, 13(2018) 9257.
23. S. Voronov, E. Frisk and M. Krysander. *IEEE Transactions on Reliability*, (2018)1.
24. C. E. Chiasserinit and R. R. Rao. *Wireless Communications & Networking Conference. IEEE*, 1999.
25. A. Eddahech, O. Briat and J. M. Vinassa. *Electrochimica Acta*, 114(2013)750.
26. X. Pang, R. Huang, J. Wen, Y Shi, J. Jia and J. Zeng. *Energies*, 12(2019)*2247.*
27. D. Liu, J. Zhou, H. Liao, Y. Peng and X. Peng. *IEEE Trans. Syst. Man Cybern. Syst*. 45(2015)915.
28. M. Lee and G. Whitmore. *Statistical Science*, 21(2016)501.
29. X. Si. *Acta Automatica Sinica*, 39(2013)530.
30. X. S. Si, W. B. Wang, C. H. Hu, D. H. Zhou and M. G. Pecht. *IEEE Transactions on Reliability*, 61(2012)50.
31. J. Zheng, X. Si, C. Hu, Z. Zhang and W. Jiang. *IEEE Transactions on Reliability*, 65(2016)736.
32. C. Peng and S. Tseng. *IEEE Transactions on Reliability*, 58(2009)444.
33. Z. Zhang, D. Shen, Z. Peng, Y. Guan, H. Yuan and L. Wu. *International Journal of electrochemical Science*, 14(2019)7149.
34. B. SAHA and K. GOEBEL. “Batterymcs date set,” NASA amesprognostics data repository [EB/OL]. [2017-11-09].http, // ti.arc.nasa.gov/project/prognostic-data-repository.
35. C. Bai, C. Hu, X. Si, H. Li, Z. Zhang and H. Pei. *Systems Engineering and Electronics*, 40(2018)114.