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# Residual Remaining Useful Life Prediction Method for Lithium-Ion Batteries in Satellite With Incomplete Healthy Historical Data

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**ABSTRACT** Due to the strict requirements of satellite systems, accurate remaining useful life (RUL) prediction of the key components is very important to the reliability and security of satellite systems. Otherwise, a failure could lead to catastrophic consequences and enormous economic losses. Because of the complex structure of the satellite and its complex space environment, the factors that affect the satellite systems status are numerous. Moreover, as a result of the healthy historical data of key components in satellite are too few, which makes the traditional methods based on analysis model are not suitable for RUL prediction of key components in satellite. In this paper, in order to solve the RUL prediction problem of Lithium-ion batteries (LIBs) in satellite with incomplete healthy historical data, we propose an efficient RUL prediction method for key components of satellite, which is called Residual Remaining Useful Life Prediction Method (RRULPM), based on the study of Multivariate State Estimation Technique (MSET). The RRULPM is make up of degradation model based on MSET state estimation and criteria of failure based on historical degradation value, which is developed by improving MSET and combining the residuals with life cycle damage (LCD) prediction creatively when lacking healthy historical data. Experimental results demonstrate that the RRULPM is excellent to achieve the RUL prediction problems of LIBs through the actual in orbit telemetry data. Unlike previous RUL prediction methods, RRULPM provides good feasibility and effectiveness. This research can serve as guidance for prognostics and health management (PHM) of key components in satellite.

**INDEX TERMS** Lithium-ion batteries, multivariate state estimation technique, remaining useful life, satellite.

## I. INTRODUCTION

As the major measures of human space exploration, aerospace technology is playing a more and more important role in military, politics, economy, technology and many other fields. Meanwhile, because of the accurate requirements of the satellite systems, so as to the satellite systems become increasingly complex than ever before. In these kinds of complex and huge investment systems, there is an urgent need to improve the reliability and security of the satellite systems. Otherwise, a failure could lead to catastrophic consequences and enormous economic losses [1]. In recent years, though there are a lot of researches have been conducted on the RUL prediction of electrical products on earth, there are few researches have been conducted on the satellite systems especially for the RUL prediction of key components in satellite. If the engine system of a satellite is the heart, then the power system of a satellite is the blood. So the power system is very important to the satellite, whose mission is to provide electrical power to the satellite, as well as to store, distribute and control the electrical power [2]. Lithium-ion batteries (LIBs) have been chosen as power suppliers for

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many systems since they were first commercially introduced by Sony in the 1990s. Compared with the traditional batteries such as nickel-cadmium battery and nickel hydrogen battery, LIBs are lighter in weight, higher in power density, and longer in cycle life. Today LIBs are widely used in portable device, marine systems, automotive vehicles and aerospace systems [3]. LIBs are mainly composed of three components: anode, cathode, and electrolyte. In the past years, most researches of LIBs focused on the design of these components [4]–[6]. However, the functionality deterioration of LIBs during operation in power system, which may cause performance degradation, money loss, and even catastrophic failure. For example, Sony lost around 430 million dollars in its global recall of 9.6 million laptop batteries [7].

### A. MOTIVATIONS

The feature of LIBs is the same as electrochemical characteristics, which is fundamentally different from the mechanical system in various aspects. First of all, the electrochemical reactions which inside the lithium-ion battery pack are difficult to monitored by using general sensor technology, resulting in the scarcity of data for analysis. Secondly, in comparison to waveform type machinery data, the most available monitoring data collected from LIBs are data-oriented such as voltage, current, and temperature. Lastly, the operation profiles of LIBs are much more dynamic than those of mechanical systems. Therefore, the development of appropriate methodologies and algorithms for the remaining useful life (RUL) prediction of LIBs must take into account the uniqueness of LIBs [8].

RUL refers to the time left before observing a failure given the current product age and condition, and the past operation profile. It is defined as the conditional random variable, $T - t|T > t, Z(t)$, where $T$ denotes the random variable of time to failure, $t$ is the current age and $Z(t)$ is the past condition profile up to the current time. Since RUL is a random variable, the distribution of RUL would be of interest for obtaining a comprehensive understanding of the RUL. In our paper, the term "Remaining Useful Life Estimate (RULE)" is referred to cover both of them. In some cases, it means finding the distribution of RUL. In some other cases, however, it just means the expectation of RUL, i.e., $E[T - t|T > t, Z(t)]$.

An efficient RUL prediction method can provide more information about the future operational status of the product. This information can be used to determine maintenance, replacement and logistics support strategies of product. The RUL can be predicted by modeling stress and damage utilizing exposure conditions coupled with failure models. In this approach, the life cycle damage (LCD) is monitored in-situ, and used in conjunction with failure-based damage models to assess the extent and rate of LIBs degradation due to cumulative load exposures. The degradation is the combination of the LIBs' electrode degradation, LIBs' electrode loss and diaphragm aging. The LCD of LIBs can be generated from manufacturing, shipment, storage, handling, operating and non-operating conditions.

Multivariate State Estimation Technique (MSET) was originally developed by Argonne National Laboratory (ANL) for high-sensitivity proactive fault monitoring applications in commercial nuclear power applications [9]–[11]. However, the traditional MSET is focus on the function in fault diagnosis by comparing the residuals with the threshold. while ignoring its ability to provide degradation information of a product. Wegerich [12] noted that MSET may be used to highlight the degradation of a monitored product. Cheng *et al.* [13] investigated the use of MSET as input in predicting the RUL prediction of electronic products. Moreover, the traditional MSET need completely healthy historical data as training data. Consequently, the traditional MSET are not suitable for key components in satellite. Reference [14] show that the MSET can be used to monitor multiple parameters of the LIBs in satellite when lack of completely healthy historical data, such as the temperature, capacity, electrolyte resistance (Re) and charge transfer resistance (Rct), and calculate the residuals between the actual and expected values of these parameters based on the healthy historic data, and achieve the fault diagnosis problems of LIBs in satellite through the actual in orbit telemetry data. However, there is no literature describes cases using MSET to do the RUL prediction of LIBs in satellite. Therefore, the main issues related to the RUL predictions of LIBs in satellite are:

- Satellite as a complex giant system and huge investment system, there is very important for its prognostic and health management (PHM). However, there are many researches on fault detection of key components in satellite, there are few researches on RUL prediction of key components in satellite. Therefore, an efficient approach for RUL prediction of key components in satellite is very important in practical engineering applications.
- As the core system of satellite, the importance of power system is self-evident. So, as the key component of energy system, the importance of LIBs is self-evident. However, because of the complex structure of satellite and its complex space environment, the factors that affect the LIBs status are numerous. Moreover, as a result of the healthy historical data of LIBs are too few, which leads to the traditional RUL prediction approaches are difficult to apply on the LIBs in satellite. Therefore, an efficient approach for RUL prediction of LIBs in satellite with incomplete historical data is very important in practical engineering applications.
- MSET is an advanced PHM method, which is a nonlinear, nonparametric modeling method for high-sensitivity proactive fault monitoring applications in commercial nuclear power applications and some other complex giant system. However, the traditional MSET is mainly used in nuclear power plants and general complex electronic systems, and it has never been used in energy systems in satellites. The mainly reason is that the traditional MSET need a large number of healthy historical

data. Therefore, an efficient approach which based on improved MSET for RUL prediction of LIBs in satellite with the actual in-orbit telemetry data is very important in practical engineering applications.

### B. SUMMARY OF PRIOR WORK

Similar to diagnosis, the approaches of RUL prediction fall into three main categories: (1) statistical approaches; (2) artificial intelligent approaches; (3) model-based approaches [15].

Goode *et al.* [16] used Statistical Process Control (SPC) to separate the whole machine life into two intervals, the I-P (Installation-Potential failure) interval in which the machine is running correctly and the P-F (Potential failure-Functional failure) in which the machine is running with a problem. Yan *et al.* [17] employed a logistic regression model to calculate the probability of failure for given condition variables and an ARMA time series model to trend the condition variables for failure prediction. Shen *et al.* [18] presented a new approach that combines transfer compact coding for hyperplane classifiers (TCCHC) with exponential semi-deterministic extended Kalman filter (EKF) to transfer the RUL prediction models among multiple working conditions.

Artificial intelligent (AI) techniques applied to RUL prediction have been considered by some researchers. Zhang *et al.* [19] used self-organizing neural networks for multivariable trending of the fault development to predict the residual life of a bearing system. Wang *et al.* [20] applied dynamic wavelet neural networks to predict the fault propagation process and predict the RUL as the time left before the fault reaches a given value. Akhand and Sanjay [21] proposed a degradation indicator based on self-organizing map for the performance degradation assessment of bearings and later support vector regression is utilized to estimate the remaining useful life of bearings. Ren *et al.* [22] proposed an integrated deep learning approach for RUL prediction of lithium-ion battery by integrating auto-encoder with deep neural network (DNN). Xiao *et al.* [23] extracted the features from condition data are divided by adaptive time windows. The time window size is adjusted according to the increasing rate.

Model-based approaches to prognosis require specific mechanistic knowledge and theory relevant to the monitored product. Ray *et al.* [24] used a non-linear stochastic model of fatigue crack dynamics for real-time computation of the time-dependent damage rate and accumulation in mechanical structures. Li *et al.* [25], [26] introduced two defect propagation models via mechanistic modeling for RUL prediction of bearings. Francesco *et al.* [27] developed a method for predicting equipment RUL, and the related uncertainty based on both complete and incomplete degradation trajectories. Luo *et al.* [28] presented an investigation into the kinematic mechanism of the passing process of the rolling element over the spall zone, and the excitation mechanism of the entry and exit responses excited by a spall located on the REB outer race is studied and the contact models of rolling element-spall interaction. Zhou *et al.* [29] proposed a dynamic opportunistic condition-based maintenance strategy for the offshore wind farm by using predictive analytics. Ahmed *et al.* [30] proposed a reliability-based prognostic methodology that uses condition monitoring (CM) data by using a pattern-based machine learning and knowledge discovery approach called Logical Analysis of Data (LAD). The LAD approach is based on an exploration of the monitored battery's database and the extraction of useful information, which describe the phenomenon of battery's degradation.

In summary, RUL prediction for system has garnered much attention in the research community in recent years. Hundreds of papers in this field, including theories and practical applications, appear every year in conference proceedings, academic journals, and technical reports. But among these researches, almost all of the approaches need amount of completely healthy historical data. Therefore, there is an urgent need for RUL prediction approach with incomplete healthy historical data. In order to solve this problem, we propose Residual Remaining Useful Life Prediction Method (RRULPM) when lack of completely healthy historical data, which use the initial actual in-orbit telemetry data as the initial training data. Then through the continuation of anomaly detection, the initial training data could update, which will get the healthy states into the initial training data and then will make the training data contain all dynamic change states of monitoring subject.

### C. OUR APPROACHES AND CONTRIBUTIONS

In this paper, based on the RUL prediction problem of LIBs in satellite, we propose RRULPM for LIBs in satellite with incompletely healthy historical data based on the degradation model and criteria of failure of LIBs. The degradation model is creatively combining the residuals with life cycle damage (LCD) prediction when lack of healthy historical data. The main contributions of this paper are as follows:

- we propose an efficient RUL prediction method for LIBs of satellite, which is called Residual Remaining Useful Life Prediction Method (RRULPM), and it is make up of degradation model based on MSET state estimation and criteria of failure based on historical degradation value.
- For the first time, we used the improving MSET to study the RUL prediction of LIBs in satellite.
- Based on the study of MSET, we improved the method of MSET with incomplete healthy historical data, considering it is difficult to obtain a large amount of historical healthy data of LIBs in satellite.
- According to practical engineering applications, we detailed introduced the key technologies of MSET and the creation steps of the degradation model and criteria of failure.
- We conducted quantitative measurement experiment to validate the feasibility and effectiveness of the RRULPM by creatively combining the residuals with LCD prediction when lack of healthy historical data.

The rest of this paper is organized as follows. The failure analysis of LIBs is presented **in Section 2**. **Section 3** discusses the key technologies of improving MSET. **Section 4** describes the RRULPM process based on improving MSET. **Section 5** provides the RRULPM result of LIBs by an experimental study. **Section 6** presents the conclusion and recommendations for future work.

## II. FAILURE ANALYSIS OF LIBs

Before using the MSET to describes the RUL prediction model of LIBs, the sticking point parameters of LIBs should be selected. So firstly we should study the failure analysis of LIBs. The LIBs are not the same as the ordinary chemistry power supply, which the charging and discharging operation are done by insertion and extraction of the LIBs' positive and negative. When the LIBs are charging, the positive electrode emancipates the lithium-ion in the electrolyte, which is called extraction, and then the negative electrode intakes the lithium-ion from the electrolyte, which is called insertion. In a similar way, when the LIBs are discharging, the procedure occurs opposite to the above process. Therefore, the process of charge and discharge that lithium-ion round-trip insertion and extraction are like a rocking chair swaying, and that is the reason that the LIBs are always called "rocking chair battery".

According to analyzing the failure mechanism of LIBs, we knew that the failure of LIBs can be separated into internal failure, external failure, and thermal runaway. However, on the basis of chemical reactions of LIBs during charging and discharging, the internal failure of LIBs is caused by three main aspects [31]: (1) Degradation of the electrode performance; (2) Loss of the electrolyte; (3) Aging of the diaphragm. The curing of cathode active ion and the growth of solid electrolyte interphase (SEI) are the main factor of electrode performance degradation of LIBs [32], [33]. Moreover, with the charge and discharge times of LIBs increase, the electrode material is oxidized corrosion which will inescapably consume part of the electrolyte, and ultimately lead to the scarce of electrolyte. And the role of diaphragm is to separate the positive and negative of LIBs, which is to prevent short-circuiting of poles. But in the recycling process of LIBs, the diaphragm is gradually aging, which is a major cause of performance degradation in the early time. These aspects that cause the internal failure of LIBs all result in the rise of internal resistance. The external failure of LIBs is the effect of many factors, in addition to the impact of its own structure, but also with the usage (i.e., the use procedure, the environment, the charge and discharge mechanism, the lithium-ion electric stress and so on.). As the thermal reaction between the electrolyte and the electrode material, which eventually lead to a devastating accident, called "thermal runaway", and the safety level of LIBs is determined by its primary temperature [31]. Generally, the thermal runaway is caused by various non-normal operating conditions, such as the temperature is too high, accidental overcharge, extrusion, internal or external short-circuit and so on. However, the external failure and thermal runaway can be controlled by ourselves in a way, so in this paper, we assume that the main failure cause of LIBs is determined by internal failure. In other words, the failure of LIBs is caused by the rise of internal resistance.

Study shows that the LIBs as a power source carrier can be equivalent to a continuous voltage source and a resistor in the ideal electrical calculation, and the expression of LIBs is closely associated to the impedance change [31]. Therefore, according to the working philosophy of LIBs research, the impedance equivalent circuit model of LIBs is shown in **Fig. 1**, where $L$ indicates the inductance and Re indicates the electrolyte resistance and $\theta$ indicates the charge transfer resistance and $C_{DL}$ indicates the capacitance of the electrode polarization and $Z_w$ indicates the Warburg impedance. In general, $\theta+$ and $\theta-$ are indicated by Rct. So the internal resistance of LIBs is indicated by Re and Rct. In practical engineering applications, the Re and Rct can be considered as electrochemical impedance spectroscopy (EIS) method.

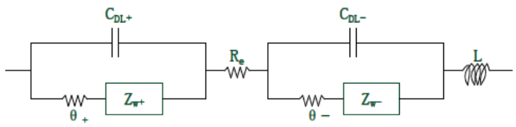


**FIGURE 1.** Impedance equivalent circuit model of LIBs.

In a word, according to the failure analysis of LIBs, the rise of internal resistance results in the failure of LIBs. Moreover, by means of the impedance equivalent circuit model of LIBs, we knew that the internal resistance of LIBs is represented by Re and Rct. Consequently, the Re and Rct are selected as the key parameters of LIBs.

## III. MSET APPROACH WITH INCOMPLETE DATA

The traditional MSET uses pattern recognition from completely healthy historical product data to produce an estimate of the current state. And the completely healthy historical data are assumed to cover the entirely healthy range of the product. So the results of MSET state estimation are the residuals, which are the difference between the actual monitored data and the expected healthy values. However, Because of the complex structure of the satellite and its complex space environment, the factors that affect the satellite systems status are numerous. Moreover, as a result of the healthy historical data of key components in satellite are too few, which makes the traditional MSET are not suitable for the key components in satellite. In order to solve these problems and let the MSET better apply to the RUL prediction of LIBs in satellite, we improved the MSET in practical engineering applications, just as the bibliography [14].

Then let us briefly review some definitions involved in MSET include the observation matrix of monitoring parameters: $X_{obs}$, the training data: $T$, the memory matrix: $D$, the remaining training data: $L$, the estimation of observation: $X_{est}$, and the estimation of remaining training data: $L_{est}$.

The state or observation $X_{obs}$ of the product at time $t_i$ is represented by a vector $X(t_i)$ or $X_{obs}(t_i)$ of length $n$, where $n$ is the number of monitored parameters of the product.

$$X(t_i) = [x_{1i}, x_{2i}, \ldots, x_{ni}]^T, \tag{1}$$

where $x_{ji}$ is the measuring of parameter $j(j = 1, 2, \ldots, n)$ at time $t_i$.

The time series signals of $i$ parameter is represented by $X_i(t_j)$ of length $m$, where $m$ is the number of time or state of the observation matrix.

$$X_i(t_j) = [x_{i1}, x_{i2}, \ldots, x_{im}], \tag{2}$$

where $x_{ij}$ is the measurement of parameter $i$ at time $t_j(j = 1, 2, \ldots, m)$.

Training data $T$ is a matrix that includes of many healthy historical states. It can be defined by the matrix format:

$$T = [\underbrace{X(t_i), \ldots, X(t_l)}_{\text{k}}, \ldots], \tag{3}$$

where $k$ is the number of states selected for the training data, which is artificial decided.

However, in practical engineering applications, according to the actual in-orbit telemetry data we assume that the initial data of LIBs which obtained from the actual in-orbit telemetry data is healthy data, in order to resolve the lack of healthy historical data problem. So we consider the initial data as the primary training data $T$. Obviously, in order to ensure the states contained in the primary training data $T$ are healthy states, the selected portion of states should be as few as possible. After that, in order to fulfill the requirement of training data $T$ that should contain completely healthy historical states as many as possible, the primary training data $T$ should update, which will make the training data $T$ contain all dynamic change states of monitoring parameters. The meaning of update is to get the healthy states into the primary training data $T$ with the continuation of anomaly detection, and the anomaly detection based on MSET just as shown in reference [34]. However, there are two methods for the update of training data T just as follows:

- Non-quantitative update method (NQUM).With the continuation of anomaly detection, add the healthy states into the primary training data $T$.
- Quantitative update method (QUM).With the continuation of anomaly detection, only add the healthy states in the floating window into the primary training data $T$.

According to comparing the two update methods, the more states contained in the NQUM, the better state estimation effect of the NQUM might be. However, in practical engineering applications, the requirements on control of time delay during data processed and the requirements on latency and bandwidth during communication should be considered. Because of the actual in-orbit telemetry data of LIBs are extremely large. Therefore, the time delay and the latency of the NQUM would be long. As a matter of fact, according to practical engineering test, the QUM not only can fulfill the requirement of training data $T$, but also can greatly reduce the time delay and the latency. Consequently, considering the calculated amount in practical engineering applications, the QUM is more practical than the NQUM. Then the training data $T$ are updated by QUM, and the traditional MSET are improved when lack of completely healthy historical data.

Memory matrix $D$ include of special states selected by **Algorithm 1** from training data $T$. **Algorithm 1** is the pseudocode of creating memory matrix $D$ algorithm, where the input conditions are the training data $T$ and the number of the states contained in the memory matrix $D$ and the output result is the memory matrix $D$. After the training data $T$ has been selected and $k_1$ is artificially determined, the MSET will select some special states from the training data $T$ to create memory matrix $D$. First of all, the states that contain the extreme states of monitoring parameters (minimum and maximum value of each parameter) are selected because they contain the extreme features of the subject. The detailed steps are as follows: first calculate the row and column of training data $T$, where $n$ represents the row of training data $T$, $k$ represents the column of the training data $T$; Second calculate the inverted matrix of training data $T$, $T_{back}$; Third when the $i$ from 1 to $n$ calculate the order number of maximal value in vector $T_{back}$(i), which is defined as $E_{max}$(i), and calculate the order number of minimal value in vector $T_{back}$(i) which is defined as $E_{min}$, and set the order number of most value in $T_{back}$(i) as vector $E_{dis}$; Fourth delete the same number in vector $E_{dis}$, and the vector $E$ represents the extremely states of monitoring parameters in training data $T$. Secondly if the number of extremely states is equal to $k_1$, the process of creating memory matrix $D$ is accomplished, and the states contained in memory matrix $D$ are the extreme states of monitoring parameters in training data $T$. Otherwise, there are two possibilities: if the number of extreme states outnumber $k_1$, and then Print "Please try to reenter a bigger number $k_1$"; If the number of extreme states cannot outnumber $k_1$, and then the algorithm continues to select additional states from the remaining training data $T$ in the following steps: First select the extreme states of monitoring parameters in training data $T$, and then get $D_{extre}$; Second execute another $T$, $T_{copy}$; Third delete the extreme states of monitoring parameters in training data $T$; Fourth, the number of rest states contained in memory matrix $D(k_1)$ minus the extreme states of monitoring parameters in training data $T(E_{num})$, and get $D_{numb}$; Fifth, the number of rest states contained in training data $T(k)$ minus the extreme states of monitoring parameters in training data $T(E_{num})$, and get $k_{rest}$; Sixth when the $i$ from 1 to $k_{rest}$, calculate the Euclidean norm of remaining training data $T$, which is defined as $T_{norm}$; Seventh arrange the vector $T_{norm}$ by ascending, where $T_{sort}$represents the remaining training data $T$ after ascending and $I$ represents the states position after ascending. Lastly, the algorithm selects the additional states with equally spaced intervals from the ordered states until the amount in column $D$ reaches the user-specified number of states $k_1$. If $k_1$ amount of states from training data $T$ is selected, memory matrix $D$ can be defined as

$$D = [X_1, X_2, \ldots, X_{k_1}], \tag{4}$$

where $X_i$ is one of the states selected from the training data $T$, $k_1$ is the number of states.

**Algorithm 1** Pseudocode of Creating Memory Matrix D Algorithm

**Require:** $T, k_1$
**Ensure:** $D$
$size(T) \rightarrow [n, k]$.
$T' \rightarrow T_{back}$.
**for** $i = 1$ to $n$ **do**
  $max(T_{back}(i)) \rightarrow [y, E_{max}(i)]$
  $min(T_{back}(i)) \rightarrow [y, E_{min}(i)]$
  $E_{max(i)}, E_{min(i)}] \rightarrow E_{dis}$
**end for**
$unqiue(E_{dis}) \rightarrow E$
$size(E) \rightarrow E_{num}$
**if** $thenE_{num} > k_1$
  Print "Please try to reenter a bigger number $k_1$"
**else if** $thenE_{num} = k_1$
  Print $T(:, E) \rightarrow D$
**else**$E_{num} < k_1$
  $T(:, E) \rightarrow D_{extre}$
  $T \rightarrow T_{copy}$
  $T_{copy}(:, Enum) \rightarrow []$
  $(k1 - E_{num}) \rightarrow D_{numb}$
  $(k - E_{num}) \rightarrow k_{rest}$
  **for** $i = 1$ to $k_{rest}$ **do**
    $norm(T_{copy}(:, i)) \rightarrow T_{norm}$
  **end for**
  $sort(T_{norm}) \rightarrow [T_{sort}, I]$
  $T_{copy}(:, I(1 : k_{rest}/D_{numb} : length(I))) \rightarrow D_{rest}$
  $[D_{extre}, D_{rest}] \rightarrow D$
**end if**

States in the training data $T$ that are not only selected for the memory matrix $D$, but also for the remaining training data $L$. The remaining training data $L$ is a matrix of $n \times k_2$, where $n$ indicates the number of monitoring parameters and $k_2$ is the number of the states contained in the remaining training data $L$. So the remaining training data $T$, the memory matrix $D$, and the remaining training data $L$ have the following equation relationship,

$$T = D \cup L. \tag{5}$$

The estimate of observation matrix $X_{obs}$ is described as $X_{est}$, which is the expected value calculated from the training data. This estimate has the same data format as the observation, which is an n-element vector that is thought to be the weighted (linear) combination of states in memory matrix $D$. In the same way, the estimate of remaining training data $L$ is described as $L_{est}$.

When the monitoring parameters of LIBs are selected, the new observation matrix $X_{obs}$ can be acquired from the actual data. And then as mentioned before, healthy data from initial data of actual in-orbit telemetry data could be chosen as training data $T$, and special data from the training data $T$ are picked to create memory matrix $D$ according to **Algorithm 1**. After the memory matrix $D$ is created, MSET will go through two processes. One is to calculate estimates ($L_{est}$) of all the remaining training data $L$, which the states are not chosen as in the memory matrix $D$ though they are in training data $T$. Then the MSET calculates the residuals between the estimates ($L_{est}$) and remaining training data $L$. Because of all these states contained in the remaining training data $L$ are defined as healthy states, so the residuals present the features of healthy states in LIBs, which are called healthy residuals and defined as $R_L$. After that the MSET calculates the estimates ($X_{est}$) of the new observation matrix $X_{obs}$, the residuals are the difference between the estimates and the corresponding observations, and due to the residuals are the difference between the actual states and estimate of actual states of the LIBs, so the residuals are called actual residuals and defined as $R_X$.

The calculation equation of $X_{est}$ is

$$X_{est} = D \cdot W, \tag{6}$$

where $W$ is a weight vector, which decides a similarity measure between each state in memory matrix $D$ and the estimation matrix $X_{est}$. The formula for this vector is derived from the least square method by minimizing the error vector.

$$\varepsilon = X_{obs} - X_{est}, \tag{7}$$

when the $\varepsilon$ is constrained by minimization, the least square error estimation solution of weight vector $W$ is:

$$W = (D^T \cdot D)^{-1} \cdot (D^T \cdot X_{obs}). \tag{8}$$

So through (6), (7) and (8), the estimation matrix $X_{est}$ for the observation matrix $X_{obs}$ is

$$X_{est} = D \cdot (D^T \cdot D)^{-1} \cdot (D^T \cdot X_{obs}). \tag{9}$$

In equation (9), if the weight vector $W$ is existence, the $D^T$·D must be reversible. However, a necessary but not sufficient condition of the $D^T$·D reversible is: the number of columns of the memory matrix $D$ should be less than the number of lines of the memory matrix $D$. However, in practical engineering applications, this requirement is very difficult to be fulfilled. Therefore, in order to solve this problem, we improved the MSET method by introduced the nonlinear operator instead of Multiply, which is defined as a typical operator that calculates normalized similarity between different data vectors. In this paper, we make use of the most commonly used nonlinear operator-Gaussian operator. The Gaussian operator equations can be described as follows:

$$f(x, y, h) = \sum_{m=1}^{M} \frac{1}{\sqrt{2\pi}h} e^{\frac{(x_m - y_m)^2}{2h^2}}, \tag{10}$$

where $h$ is the filter coefficient or also known as bandwidth.

Based on this problem, a feasible way is introduction of the ridge regularization when inverse the $(D^T \otimes D)$. And then after that, the (8) and (9) can be described as follows:

$$W = (D^T \otimes D + \lambda I)^{-1} \cdot (D^T \otimes X_{obs}), \tag{11}$$

$$X_{est} = D \cdot (D^T \otimes D + \lambda I)^{-1} \cdot (D^T \cdot X_{obs}), \tag{12}$$

where $\lambda$ is the ridge regularization parameter ($\lambda > 0$), $I$ is the identity matrix.

The optimization problem of $\lambda$ is a one-dimensional optimization problem, which can be resolved by using nonlinear methods, such as conjugate gradient descent and so on. When the value of each monitoring parameter follow normal distributions with mean 0 and variance 1, the majorization bandwidth is $h = 1$, and the optimization ridge regularization is $\lambda = 1$ [26].

In the same way, the calculation equation of $L_{est}$ is

$$L_{est} = D \cdot W', \tag{13}$$

where $W'$ is also a weight vector. The same as above, the estimation matrix $L_{est}$ for the remaining training data $L$ is

$$L_{est} = D \cdot (D^T \otimes D + \lambda I)^{-1} \cdot (D^T \cdot L), \tag{14}$$

The definition of residual value is: the value that the estimated value minus the actual value. Therefore, the calculation equations of the actual residual $R_X$ and healthy residual $R_L$ are

$$R_X = X_{est} - X_{obs} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix}, \tag{15}$$

$$R_L = L_{est} - L = \begin{bmatrix} r'_{11} & r'_{12} & \cdots & r'_{1m} \\ r'_{21} & r'_{22} & \cdots & r'_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r'_{n1} & r'_{n2} & \cdots & r'_{nm} \end{bmatrix}, \tag{16}$$

where $r_{ij}$ and $r'_{ij}$ indicates the residual value of the actual residual value and the healthy residual value separately when the monitoring parameter $i$ on the state $j$.

## IV. RUL PREDICTION MODEL USING IMPROVED MSET

Reference [12] pointed out that the MSET can be used to monitor the product degradation, but there is no exact model to implement such an application. So far, there is no more formal model to apply the MSET to RUL prediction of product.

In fact, the actual residuals calculated by MSET state estimation, not only indicates whether the LIBs are in a healthy state or an abnormal state in the current state, but also relates to their relationship with LIBs degradation. If this relationship is found and their failure criteria are known, then the RUL prediction based on MSET is feasible. Therefore, in general, the establishment of the RUL prediction model based on MSET is mainly divided into the following three steps:

*Step 1:* Calculation of the actual residuals. Through the state estimation based on MSET, the actual residuals of the key monitoring parameters in LIBs are calculated.

*Step 2:* The establishment of the degradation model. According to the degradation model, the degradation value of LIBs are calculated by the actual residuals at this moment, and then according to the decline trend of the degradation value, the future degradation trend is regression simulated.

*Step 3:* The determination of the criteria of failure. The criteria of failure is the degradation value when the LIBs are failure or in the abnormal state. In this process, firstly we should select the historically-failed test LIBs which have the same failure mechanism as the actual test LIBs, and secondly we should calculate the degradation value of these historically-failed test LIBs by **Step 1** and **Step 2**. Since the failure state of these historically-failed test LIBs are known before, the degradation value of these historically-failed test LIBs in their failure states can also be calculated. Therefore, the degradation value of the historically-failed test LIBs in their failure states can be used as a criteria of failure for the RUL prediction of actual test LIBs.

Based on the above three steps, according to the RRULPM process which is shown in **Fig. 2** based on MSET, the RUL prediction of LIBs in satellite can be realized.

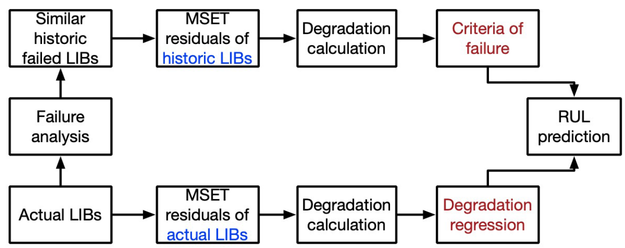



**FIGURE 2. Process of RRULPM.**

### A. DEGRADATION MODEL

When the LIBs is operating normally, the actual residual value $R_X$ between the observation matrix $X_{obs}$ and the estimated value $X_{est}$ of the observation matrix suggests the degradation of the LIBs. If the degradation of the LIBs are regarded as an accumulation process, then the accumulated degradation value at the time state $t_k$ can be regarded as the sum of the Euclidean norms of the actual residual $R_X$ from the start time 0 to the time state $t_k$, and the equation is as follows:

$$R_{accumulation}(t_k) = \sum_{i=1}^{k} \|R_x(t_i)\|, \tag{17}$$

where, $R_{accumulation}(t_k)$ is the accumulation degradation value from the start time $o$ to the time state $t_k$, and $R_{X(ti)}$ is a vector consisting of the actual residuals of all parameters at time $t_i$, and the concrete equation is as follows:

$$R_x(t_i) = [r_{1i}, r_{2i}, \ldots, r_{ni}]^T, \tag{18}$$

where,$r_{ji}$(j = 1,2,…,n) is the actual residual of parameter $j$ at time $t_i$. The Euclidean norm of the actual residual vector $R_{X(ti)}$ is as follows:

$$\|R_x(t_i)\| = \sqrt{r_{1i}^2 + r_{2i}^2 + \cdots + r_{ni}^2}, \tag{19}$$

Combining equations (17) and (19), we can see that the accumulated degradation value $R_{accumulation}(t_k)$ is the cumulative sum of the $R_{X(ti)}$ Euclidean norm, so the accumulated degradation value $R_{accumulation}(t_k)$ necessarily increases gradually as the time state increases. However, in practical engineering applications, in order to eliminate the influence of the number of time states, we can define the degradation value of the LIBs from the start time 0 to the to the time state $t_k$. and the $R(t_k)$ is as follows:

$$R(t_k) = \frac{1}{k}\sum_{i=1}^{k}\sqrt{r_{1i}^2 + r_{2i}^2 + \cdots + r_{ni}^2}, \tag{20}$$

### B. CRITERIA OF FAILURE

From the limited historically-failed test LIBs, the degradation value of the LIBs in failure conditions is calculated, and then the criteria of failure is calculated by statistical methods.

When the failure mechanism of the actual test LIBs is the same as the historically-failed test LIBs, the actual test LIBs will be failure at the same degradation value. Selecting the historically-failed test LIBs with the same failure mechanism as the actual test LIBs, and the actual residual $R_X$ of the historically-failed test LIBs in failure states was calculated by the MSET state estimation. Then, according to the (19)-(20), the degradation value in failure conditions is calculated. Finally, according to calculating the degradation value in the failure state of historically-failed test LIBs, and then the criteria of failure is calculated by statistical methods.

If the historical data of the historically-failed test LIBs is not available, the Criteria of failure can also be calculated by accelerated test. However, before the accelerated test, there is a very important premise that the failure mechanism of the LIBs does not change when the accelerated test is performed, that is, the degradation value of the failed LIBs is the same under different stresses.

In summary, according to the degradation model, the degradation value of the actual test LIBs is calculated, and according to the calculated criteria of failure, we can realize the RUL prediction of the actual test LIBs.

## V. EXPERIMENT STUDY

After these studies, we would provide the result of RRULPM in LIBs by an experimental study. It is worthy of note that the experimental data used in this paper are the experimental data of Battery Data Set provided by NASA PCoE Research Center and the experimental data of Battery Data Set provided by Advanced Life Cycle Engineering Center of University of Maryland. And the NASA's data set comes from the LIBs monitoring bed which built by NASA PCoE Research Center [35]. And the batteries are 18650 LIBs with 2 Ah rated capacity which sold in the market. And the data sets are provided in standard format *. mat file for data storage in MATLAB.

First of all, **in section 2**, we detailedly analyzed the reason for LIBs' failure from three aspects and lastly selecting the Re and Rct as the key parameters of LIBs in the RRULPM. And then according to the introduction **in section 3**, the key technologies of improving MSET in practical engineering applications are clear. From the actual in-orbit telemetry data, we successfully selected the training data $T$ and observation

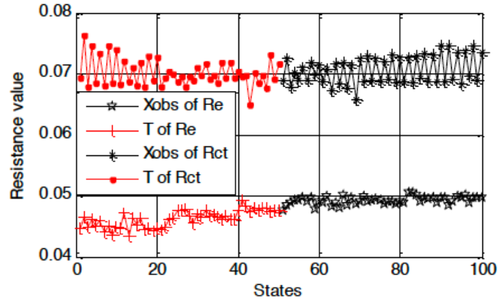



**FIGURE 3.** Training data $T$ and observation matrix $X_{obs}$.

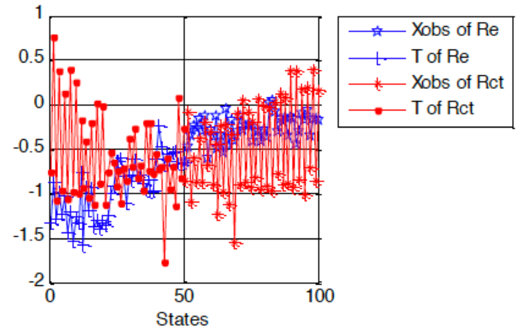
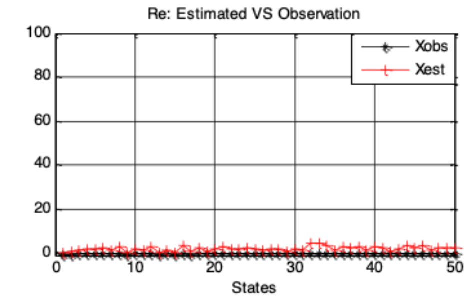



**FIGURE 4.** Training data T and observation matrix $X_{obs}$ after normalization.

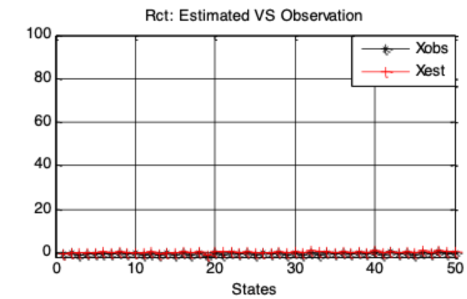
matrix $X_{obs}$ from the actual test LIBs, just as shown as **Fig.3**, we selected the previous 50 states as the training data $T$, and the latter 50 states as the observation matrix $X_{obs}$, where the red represent the training data $T$ and the black represent the observation matrix $X_{obs}$. And also in the **Fig.3**, the dot and asterisk represent the resistance value of Rct, and the plus sign and five-pointed star represent the resistance value of Re.

After that, as explained **in section 3**, the data should be normalized before state estimation based on MSET. So as seen in **Fig. 4**, where the red represent the training data $T$ and the observation matrix $X_{obs}$ of Rct, and the blue represent the training data $T$ and the observation matrix $X_{obs}$ of Re. And also in the **Fig. 4**, the previous 50 states are the training data $T$ and the latter 50 states are the observation matrix $X_{obs}$ after normalization.

And then, the estimated values of Re and Rct are computed through state estimation based on improving MSET by (11) and (12). And then a comparison of estimated value and observation value of Re and Rct, just as shown as **Fig.5**, where the left is the comparison of estimated value and observation value of Re, and the right is the comparison of estimated value and observation value of Rct, and in the **Fig.5**, the red plus sign represent the estimated matrix of observation $X_{est}$, and the black asterisk represent the observation matrix $X_{obs}$. In the **Fig.5**, we can also see some of the estimated value of Re and Rct are very larger than the after normalization observation value, the reason for that is some of the states are abnormal states, so according to the MSET study, if the state is the abnormal state, then the estimated value may larger or lower




(a) A comparison of estimated value and observation value of Re.




(b) A comparison of estimated value and observation value of Rct.

**FIGURE 5. A comparison of estimated value and observation value.**

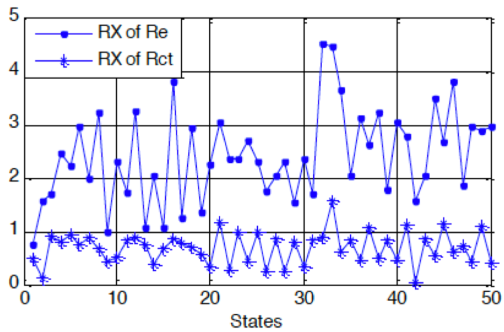
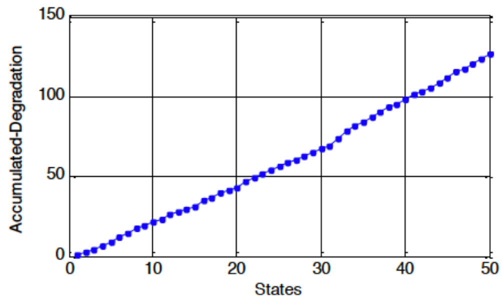
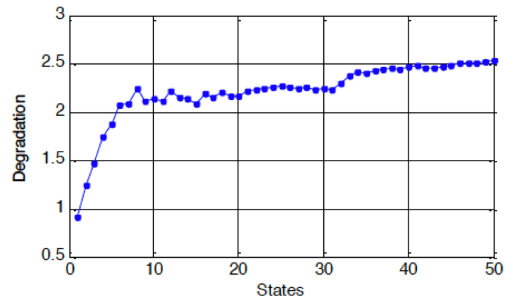



**FIGURE 6. Actual residual value of Re and Rct.**




(a) Accumulated-degradation value of actual test LIBs.




(b) Degradation value of actual test LIBs.

**FIGURE 7. Degradation of actual test LIBs.**

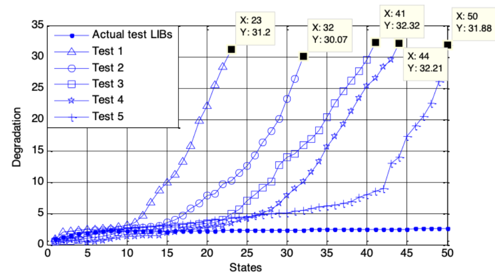



**FIGURE 8. Degradation plots of LIBs conducted during accelerated test and actual test.**

than the observation value. In other words, if the estimated value is larger or lower enough than the observation value, then the state has a high probability of being an abnormal state.

And then the actual residual values of Re and Rct are also calculated by (15) and (16), as shown as **Fig.6**, where the dot represents the actual residual value of Re and the asterisk represent the actual residual value of Rct. In the **Fig.6**, we can tell the actual residual value of Re and Rct within a certain range in 50 states. And the actual residual value of Re are larger than the actual residual value of Rct, that's because of actual resistance of Re are larger than Rct, and we do not normalize the values. That's another reason why we call the residual value are actual residual value.

After the actual residual value $R_X$ of actual test LIBs were calculated above, then as explained **in section 4**, the accumulated-degradation value and degradation value of actual test LIBs were calculated by (17) and (20), just as shown in **Fig.7**, where the left figure is the accumulated-degradation value of actual test LIBs which the value is steadily increasing and the right figure is degradation value of actual test LIBs which the value is smooth advancing since the 9 state.

And then in order to calculate the criteria of failure, we selected the same five LIBs for acceleration test. Then the same way mentioned above to calculate the actual residual $R_X$ and degradation value for these five LIBs, just as shown in **Fig.9**, where five accelerated test LIBs all failed in 50 states. In **Fig.9**, the dot represents the degradation value of actual test LIBs under normal conditions, and the others represent the degradation value of accelerated test LIBs, and the small box represent the degradation value and state when the accelerated test LIBs failed.

**TABLE 1.** Degradation value when accelerated test LIBs failed.

| Accelerated test | Failure state | Degradation |
|---|---|---|
| Test 1 | 23 | 31.20 |
| Test 2 | 32 | 30.07 |
| Test 3 | 41 | 32.32 |
| Test 4 | 44 | 32.21 |
| Test 5 | 50 | 31.88 |
| Mean | / | 31.54 |
| Stdev | / | 0.93 |

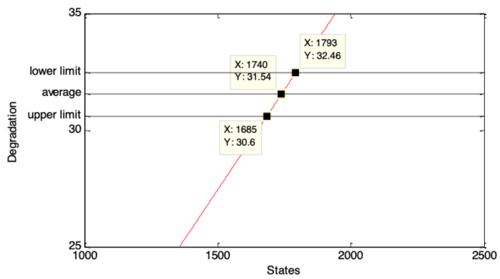



**FIGURE 9.** RUL prediction of the actual test LIBs.

From the data in **Fig.9**, the degradation value and the corresponding failure state of the five LIBs are shown in **Table 1**, where the mean and standard deviation of these degradation value were computed. In this paper, the $mean \pm \sigma$ of the degradation value of the failed LIBs was chosen as the criteria of the failure for RRULPM in the actual test LIBs.

The actual test LIBs was used under normal conditions. And assuming the actual test LIBs have the same failure mechanism as the former 5 failed LIBs. According to the **Fig.3-Fig.8**, we had known the related value of actual test LIBs. Then, the degradation value was regressed to show the future trend. In this paper, linear regression was selected to make it easy to figure out equations though it is possible to obtain more accurate trends using more complex regression models. And the prediction of the failure time of the actual test LIBs was calculated when the regressed degradation broke the criteria of failure. **In Fig.10**, the criteria of failure are in [30.60, 32.46]-the interval of $mean \pm \sigma$ of the degradation value of the five former accelerated test failed LIBs, and the red line means the linear regression of the degradation of actual test LIBs which derived from the **Fig.8**. And then according to the criteria of failure, the predicted failure time of the actual test LIBs were the interval [1685, 1793] states.

Considering it is difficult to obtain a large amount of historical healthy data of LIBs in satellite. The RUL can be predicted when the trended degradation reaches the failure criteria of the LIBs. The criteria of failure are calculated by the degradation value when the historically-failed LIBs fails, and then the criteria of failure can be estimated by statistical methods from the historically-failed LIBs, when they have the same failure mechanism with the actual test LIBs. The assumption here is that the same LIBs will fail at the same degradation value if they have same failure mechanism. The experiment study shows the whole procedures of RRULPM.

Based on the actual experimental data, the final failure state of the actual test LIBs in this experiment study is 1712, which is in the interval of the predicted time. Therefore, the significance of this experiment study lies in exploring the effectiveness of the method which based on the improving MSET and LIBs regression model, and providing a new method for RUL prediction research.

## VI. CONCLUSION

As we all know, RUL prediction for satellite is one of the core technologies that ensure satellite operating with in-orbit-safety and reliability. Owing to complex structures of satellite and its complex space environment, the factors that affect the satellite status are numerous. And due to these effects it is difficult to establish an accurate analysis model. Moreover, as a result of the healthy historical data of key components in satellite are too few, which makes the traditional methods based on analysis model are not suitable for RUL prediction of key components in satellite. To solve these problems, based on the RUL prediction problems of LIBs in satellite, we propose RRULPM (Residual Remaining Useful Life Prediction Method) of LIBs in satellite with incomplete healthy historical data, based on the study of MSET. On the basis of the actual residuals between the actual values and the expected estimates of the parameters calculated by improving MSET, the degradation of LIBs can be modeled and the trends of these degradations can be regressed by proper models (linear regression is used in this experiment study). Then the failure interval prediction demonstrates that the RRULPM is excellent to achieve the RUL prediction problems of LIBs in satellite through the actual in-orbit telemetry data. Unlike previous RUL prediction methods which need complete healthy historical data, the approach provides good feasibility and effectiveness.

The investigation in this paper is conducted from an engineering perspective. Extensive applications demonstrate that the model and algorithm are feasible, effective, and advanced. Studies on RRULPM can offer theoretical and technical guidance for prognosis and health management (PHM) of key components in satellite.

Recommendations for future work are threefold: (1) An in-depth analysis failure of LIBs in satellite should be conducted and more influencing parameters should be considered; (2) More studies on the key technologies of MSET should be carried out; (3) To serve as guidance for PHM by using RRULPM.

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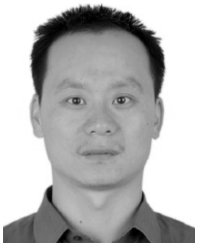

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