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State of Health Estimation for Lithium-Ion Battery Using Empirical Degradation and Error Compensation Models

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ABSTRACT State of health (SOH) estimation is always an important factor in ensuring the reliability and safety of lithium-ion batteries. In view of the shortcomings of the existing SOH estimation methods, such as non-universal, the estimation of different batteries is limited, and the accuracy is insufficient. A fusion estimation method that depends on an empirical degradation model and a data-driven method is proposed. First, we construct an empirical degradation model of lithium-ion battery SOH with charge-discharge cycles. Four working condition characteristics are extracted from the actual charging and discharging process of batteries. Then, with these features as inputs, the prediction error of the empirical degradation model is taken as the output, and training the error compensation model becomes dependent on the data-driven method. The actual working condition characteristics of the tested lithium ion battery are substituted into the training error compensation model, and the model output is fed back to the prediction results of the empirical degradation model. A high-precision estimation of lithium-ion battery SOH is thereby achieved. Finally, the proposed method is verified based on the NASA lithium-ion battery data set. The results show that the fusion method is applicable to different lithium-ion batteries of the same type, and the mean absolute percentage error of SOH estimation is approximately 2%, indicating that the proposed method exhibits good estimation performance and applicability.

INDEX TERMS Lithium-ion battery, state of health, empirical degradation model, error compensation model, data-driven method.

I. INTRODUCTION

Lithium-ion batteries are widely used in electric vehicles, communication equipment, aerospace and other fields due to their high energy density, long cycle life and high safety performance [1]–[3]. As lithium-ion batteries are the core component of these systems, battery failure will affect the normal operation of the whole system and even lead to serious accidents and economic losses. The state of health (SOH) estimation of lithium-ion batteries can effectively evaluate the degree of performance degradation and provide an important assurance for the stable operation of the power system.

Currently, the SOH estimating methods for lithium-ion batteries are mainly divided into three categories: model-based, data-driven and fusion-based methods. The model-based methods mainly include electrochemical models [4]–[7], equivalent circuit models (such as the Thevenin model [8], [9], RC model [10]–[14], etc.) and empirical degradation models [15], [16]. Electrochemical and equivalent circuit models are based on the internal physicochemical properties of lithium-ion batteries. The models are used to simulate the dynamic characteristics and degradation process of lithium-ion batteries, and combined with model parameter identification algorithms (such as extended Kalman filter [5], [12], adaptive sliding mode observer [11], etc.) to achieve estimation. The electrochemical model provides high estimation accuracy and clear physical meaning, but because of the excessive parameters and the overly complicated equations, it is difficult to calculate, so the practical application is difficult. The equivalent circuit model exhibits

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good applicability to the various working states of power batteries, and the state equation of the model can be derived. The characteristics of simple structure and clear physical meaning make equivalent circuit models the most widely used in engineering. However, electrical components can only simulate the terminal voltage output characteristics of the battery, and are generally used for SOC estimation, and cannot truly reflect the corresponding physical and chemical processes inside the battery. The SOH estimation method based on an empirical degradation model requires that a mathematical model is established from the perspective of data characteristics (such as a polynomial model based on capacity degradation data [17], an exponential model [17]–[19], etc.) to describe the degradation process of lithium-ion batteries. Empirical degradation models have specific mathematical expressions that are intuitive and simple. However, an accurate mathematical model is difficult to establish because lithium-ion batteries are complex dynamic nonlinear system. The impacts of the uncertain working conditions, such as external operating environments and charging and discharging mechanism, etc., are not considered in these models, and their dynamic accuracy is limited to a certain extent. In summary, the complex degradation mechanism and prior experience of lithium-ion batteries are the foundations of the model-based method. With the rapid development of machine learning and intelligent algorithms, data-driven methods are widely used in lithium-ion battery prognostic and health management (PHM). Data-driven methods do not need to pay attention to the failure mechanism of the lithium-ion battery, which derives solely from the perspective of historical degradation data and monitoring data, using statistical and machine learning algorithms(such as neural networks [20], [21], Gaussian process regression [22], [23], extreme learning machine [24], etc.) to train a "black box" model, and then estimate the battery SOH through the trained model. The data-driven methods need to rely on a large amount of modeling data samples, and the prognostic process is consistently opaque [25]. In addition, the trained ''black box'' model is only valid for the test battery and is not applicable to other battery data. The robustness and universality are poor. Compared with data-driven model-based methods, these methods are generally more stable. To complement the advantages and disadvantages of different methods, the fusion method provides a new concept for achieving high-precision SOH estimation and prognosis. Guha and Patra [26] proposed a fusion estimation model that combines a model of capacity degradation and internal resistance growth. The fusion model has higher growth model estimation accuracy than a single model or capacity degradation resistance. Yu [27] provided a method for estimating SOH regression model based on multi-scale logistic regression and Gaussian processes. Empirical mode decomposition is first used for feature extraction of the battery raw capacity sequence. The logistic regression model is used to fit the global degradation trend of the battery. The local regeneration and uncertainty fluctuation in the degradation process is estimated recursively by the Gaussian process regression model. The proposed fusion scheme comprehensively considers the time-varying degradation behavior of the lithium-ion battery. In Ref. [28], a battery SOH estimation system based on state-space model was given, which combines with logistic regression (LR) and particle filter (PF) algorithm to achieve prediction. Xing *et al.* [29] established a comprehensive model combined with the experience exponential model and polynomial regression model, and applied PF algorithm to predict the remaining useful life (RUL) of lithium-ion batteries. Liu *et al.* [30] proposed a prognostic framework that combines a data-driven method with a model-based PF method. Based on the prediction results of the data-driven method, the PF algorithm is used to update the model parameters online; thus, the long-term prediction performance is improved. Li and Xu [31] proposed a novel integrated approach based on a mixture of Gaussian process (MGP) model and PF for lithium-ion battery SOH estimation under uncertain conditions. The fusion approaches compensate for the limitations of a single method to some extent and have become the research trend of SOH estimation for lithium-ion batteries.

Because of the differences in inherent degradation characteristics and actual working environments, the degradation process can be quite different even for the same type of battery. The uncertainty of changes in the internal failure mechanism and working conditions (including charge and discharge current, voltage, ambient temperature, etc. [32]) of lithium-ion batteries during their actual operation have a nonnegligible effect on the degradation process. This makes accurate SOH estimation more difficult. Because of the deficiencies of previous methods for estimating the SOH, as different battery estimates are limited and lack precision, a method is proposed for a fusion degradation model based on the empirical degradation model and a data-driven method. First, an SOH empirical degradation model and its charge-discharge cycle for lithium-ion batteries is constructed. The empirical degradation model is used to describe the overall degradation trend of a certain type of battery, and then the degradation difference is explained by the error compensation model. Four working condition features are extracted from the actual battery charging and discharging processes. The Pearson's Correlation Coefficient (PCC) is used to verify the strong correlation between the selected features and the battery health status, which indicates that these features are included the influence of the internal and external factors on battery degradation, which can be well used to describe the difference of degradation for batteries. The error-compensation model based on the data-driven method (e.g., Neural Network) is trained by using the extracted working condition features as the input and the empirical degradation model prediction error as the output. The error estimated value from the error compensation model is fed back to the prediction result of the empirical degradation model, thereby achieving a high-precision estimation of lithium-ion battery SOH. The proposed method comprehensively considers the impact of the degradation difference

TABLE 1. Comparison of SOH methods.

Categories	Method	Advantage	Disadvantage
Model-based	Electrochemical model[4]	Accurately predict battery capacity fade and voltage profile as a function of cycle number over a broad temperature range.	Lithium plating without considering interaction with the other and side reactions.
	Equivalent circuit model[11]	Effectively improves the estimation performance of SOC and SOH, and avoid the chatter effect.	The relationship between SOH and other effects is not considered, such as the number of cycles, temperature, etc.
	Empirical degradation model[16]	The empirical degradation models have specific mathematical expressions, which are intuitive and simple.	Parameter initialization takes too much time to affect the real-time performance of the algorithm.
Data-driven	-	Data-driven methods do not need to pay attention to the failure mechanism of the lithium-ion battery.	Data-driven methods need to rely on a large amount of modeling data samples.
Fusion-based	-	Supplements a description of the degradation differences of different batteries, and improved the applicability and accuracy of SOH estimation on different batteries of the same type.	No experimental verification of battery degradation under complex operating conditions (such as different discharge rates, different temperatures, etc.)

and has good applicability for the same type of battery. The advantages and disadvantages of the method proposed in this paper and the model-based, data-driven and fusion-based methods are shown in Table 1.

The rest of this paper is organized as follows. In Section 2, the empirical degradation model of lithium-ion battery and the error compensation model based on the data-driven method are described in detail. Then, the overall experimental framework based on the fusion estimation model is given. Based on the National Aeronautics and Space Administration (NASA) lithium-ion battery data set, the experimental results are presented in Section 3 along with a discussion. Finally, Section 4 draws conclusions and states the directions for further development.

II. EXPERIMENT

SOH is a measurement that reflects the battery performance and health status that describes current battery performance versus performance under ideal conditions and the performance of new batteries [33]. It may be described by several performance parameters such as capacity, cycle number, internal resistance [23] and so on. In this study, SOH is defined by using battery capacity as follows:

$$h(c) = \frac{Q_C}{Q_{new}} \tag{1}$$

where h represents SOH, C is the charge and discharge cycle, Q_C is the maximum usable capacity under cycle C and Q_{new} is the initial capacity of the battery.

A battery system can be divided into unknown and descriptive part, of which only the descriptive part can be described by the different models, e.g., electrochemical models, equivalent circuit models and empirical degradation models. The establishment of the first two models depends on the complex physical and chemical mechanisms of the lithium-ion battery. While the empirical degradation model established from the perspective of data characteristics do not need much knowledge of lithium-ion battery. However, due to excessive influencing factors, the empirical degradation model has difficulty accurately describing the real degradation process of batteries. In addition, during the process of empirical degradation model establishment, the actual battery system is partly simplified. These simplifications lead to modeling errors between the empirical degradation model and the actual system, which belongs to the unknown part of the battery system and is the result of the uncertainties of intrinsic and external influencing factors. Therefore, the influences of uncertainties can be eliminated by estimating the errors between the empirical degradation model and the actual system. As long as the errors are accurately acquired, error compensation for the prediction results of empirical degradation models can be performed to greatly improve the SOH estimation accuracy. A neural network (NN) can be used as a modeling error estimators due to its many characteristics, which can supplement the uncertain information that the empirical degradation model fails to describe. In this paper, the uncertain information considered mainly refers to working conditions during the battery charging-discharging stage. Therefore, the principle of the proposed fusion estimation method based on empirical degradation model and data-driven method is shown in Fig. 1.

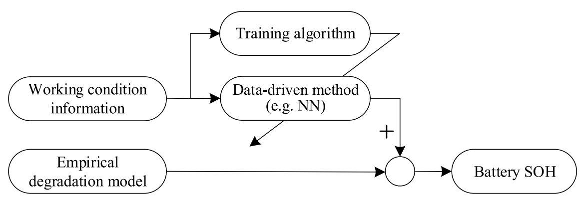

FIGURE 1. Principle block diagram of the fusion estimation method.

A. EMPIRICAL DEGRADATION MODEL

The actual capacity (AC) of the battery refers to the electrical energy that can be stored when the battery is fully charged under corresponding cycles. Because AC attenuation is the main characteristic of lithium-ion battery degradation, the SOH can be predicted by achieving the AC trend. Existing battery SOH empirical degradation models are often built from the perspective of curve fitting, such as exponential models based on capacity degradation and polynomial models [17]. The establishment of the model lacks a certain theoretical derivation process. Since differential equations have the ability to describe dynamic changes, this paper starts from the perspective of degradation rate, describing the decay process by establishing an empirical degradation model of battery capacity with its charge and discharge cycle. The degradation rate of AC as the function of AC and its cycle can be described as:

$$\frac{dQ}{dC} = f(Q, C) \tag{2}$$

where Q is the AC of the battery, $f(\cdot)$ is a nonlinear function with two independent variables. A functional expansion of $f(\cdot)$ is performed by the Taylor series of multivariate functions, and then the high-order terms are omitted. Therefore, the degradation rate of AC is given by:

$$\frac{dQ}{dC} = a_1 Q + a_2 C \tag{3}$$

where a_1 is degradation factor and a_2 is the fatigue damage accumulation factor. Solving differential Eq. (3) gives the following two solutions:

$$Q = -\frac{a_2}{a_1}C - \frac{a_2}{a_1} + \frac{1}{a_1^2}e^{a_1 C} + \delta \tag{4}$$

$$Q = -\frac{a_2}{a_1}C - \frac{a_2}{a_1} - \frac{1}{a_1^2}e^{a_1 C} + \delta \tag{5}$$

where δ is a constant.

Eq. (4) and (5) can be unified to the following form:

$$Q = b_1 C + b_2 e^{\alpha C} + b_3 \tag{6}$$

Eq. (6) is the empirical degradation model that describe the relationship between Q and C, where α, b_1, b_2 and b_3 are unknown parameters. By dividing both sides of Eq. (6) simultaneously by the initial battery capacity Q_{new}, according to Eq. (1), the SOH can be given as:

$$h = k_1 C + k_2 e^{\alpha C} + k_3 \tag{7}$$

where α, k_1, k_2 and k_3 are unknown parameters. For $C = 0$, i.e., the initial charge and discharge cycle, $h = 100\%$. Thus, the proposed empirical degradation model satisfies the following constraint:

$$k_3 = 1 - k_2 \tag{8}$$

SOH can thus be formulated as:

$$h = k_1 C + k_2 e^{\alpha C} + 1 - k_2 \tag{9}$$

Eq. (9) is the empirical degradation model that describe the relationship between h and C. Unknown parameters α, k_1 and k_2 contain a variety of factors that affect the battery degradation, which can be obtained by parameter identification algorithm. Commonly used parameter identification algorithms include maximum likelihood method, least squares method, multivariable system method,etc. Based on the outstanding performance of the least squares method in curve fitting, the least squares algorithm is taken in this paper as the algorithm basis for parameter identification of empirical degradation model. However, the empirical degradation model is based on the simplification of the actual battery system, and the description of the real battery degradation process is not so accurate. The empirical degradation model can only describe the global degradation trend of batteries, which presents the descriptive part of battery system, while the unknown part is reflected in the error between the empirical degradation model and the actual system. Thus, the error compensation model is adopted to revise the results of empirical degradation model.

B. ERROR COMPENSATION MODEL BASED ON DATA-DRIVEN METHOD

1) WORKING CONDITION FEATURES EXTRACTION WITH MONITORING PARAMETERS

The constant current constant voltage charging mode [34] is the most commonly used charging mode for lithium-ion batteries. This means that the batteries are charged by the constant current mode so that their voltages gradually rise to the cutoff voltage level, and then the constant current charging mode is switched to the constant voltage charging mode. Fig. 2 shows the complete charging and discharging process of a lithium-ion battery, including the constant-current charging stage, the constant-voltage charging stage and the constant-current discharging stage. The battery is charged with a constant current of 1.5A until the voltage reaches 4.2V. Then, the batteries are maintained in a constant voltage charging mode until the charge current falls to 20 mA. Finally, the discharge phase is run at a constant current level of 2A until the battery voltage drops to 2.7V. At the end of the constant-current discharge stage, there will be a certain voltage recovery behavior.

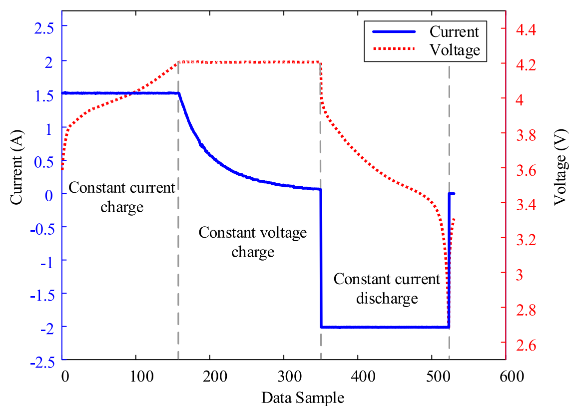

FIGURE 2. Charging-discharging process of lithium-ion battery.

The aging of lithium-ion batteries is usually reflected by changes in charge and discharge. An example is shown in Fig. 3. Three different charging-discharging cycles were extracted from the 50th, 100th and 150th cycle of the same lithium-ion battery. It can be seen that during the charging stage, the constant-current charging time of the battery decreases with the increase in cycles, and the time for the charging voltage to reach the cutoff voltage level is shortened

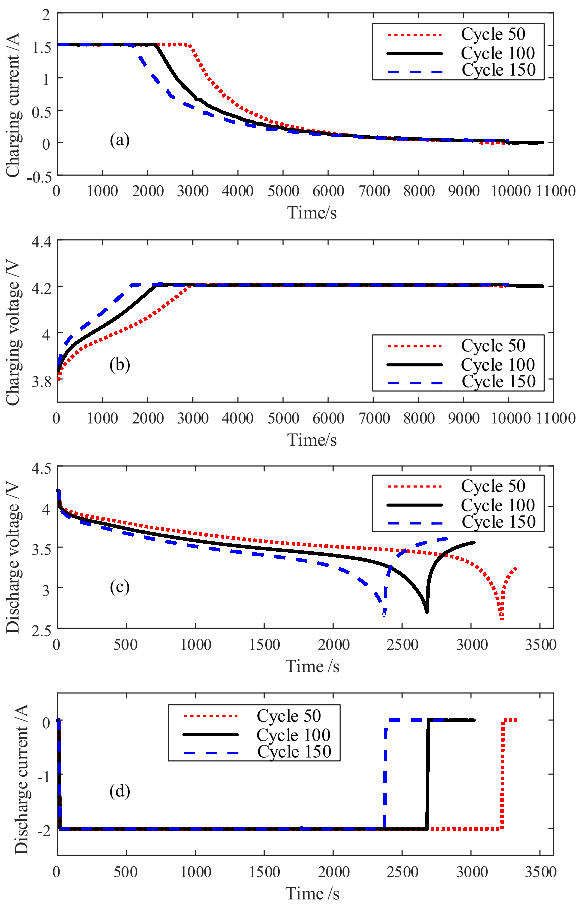

FIGURE 3. Charging-discharging current and voltage curves during different cycles: (a) charging current; (b) charging voltage; (c) discharge voltage; (d) discharge current.

correspondingly. During the discharge stage, with the degradation of the battery, the constant-current discharge time decreases, and the time to reach the discharge cutoff voltage decreases accordingly. These results indicate that the difference in current-voltage curves in different periods contain much information related to the health status of batteries.

In more intuitively characterize the difference of charging-discharging current and voltage in different cycles, the average values of charging-discharging current and voltage curves are extracted as the working condition features of the current cycle of batteries, which are average charging current, average charging voltage, average discharge current and average discharge voltage.

To verify the effectiveness of battery degradation quantization using the extracted operating condition characteristics, we perform the Pearson's Correlation Coefficient (PCC) to compare and determine the similarity between these features and the battery SOH. Thus, four quantitative features can be extracted from the battery on-line monitoring time series stored in the data file. The evaluation process with the PCC algorithm can be described as follows:

Step 1: Prepare a validated series and recommended series. The validated series is defined for the selected working condition feature series, defined as $X_i = \{x_i(k)|k = 1, 2, \cdots, n\}$, $(i = 1, 2, \cdots, m)$, and the referred series is the SOH series defined as $Y = \{y(k)|k = 1, 2, \cdots, n\}$, ($n$ is the length of series and m is the number of verified series);

Step 2: Calculate the correlation coefficient. The correlation coefficient of X_i and Y is:

$$\rho_{X_i,Y} = \frac{COV(X_i, Y)}{\sigma_{X_i}\sigma_Y} \tag{10}$$

Among them, $COV(X_i, Y)$ represents the covariance of X_i and Y. σ_{X_i}, σ_Y are the standard deviation of X_i and Y, respectively. Generally, the correlation intensity of variables is judged by the range of the absolute value of $\rho_{X_i,Y}$: 0.0-0.2 denotes extremely weak correlation or no correlation; 0.2-0.4 denotes weak correlation; 0.4-0.6 denotes moderate correlation; 0.6-0.8 denotes strong correlation; 0.8-1.0 denotes extremely strong correlation.

2) ERROR COMPENSATION MODEL BASED ON BP NEURAL NETWORK ALGORITHM

The complexity of the lithium-ion battery operating environment results in battery SOH not showing a simple linear attenuation trend, and the influence of uncertain factors is not negligible. Although the empirical degradation model can describe the overall degradation trend of battery performance, it fails to accurately describe the actual degradation state of batteries. Therefore, it is necessary to supplement the prediction results of the empirical degradation model with the error compensation model. Due to the strong nonlinear mapping ability of BP neural network (NN) and its excellent performance in self-learning, self-adaptation and generalization ability, the BP neural network is selected as the algorithm basis of the error compensation model. The model is trained by using the working condition features extracted from the actual battery charging-discharging process as inputs and the errors between the empirical degradation model and the actual battery as outputs. The steps of the proposed error compensation model based on BP NN are described as follows.

Suppose M lithium-ion batteries; the samples, i.e., working condition features during the charge-discharge phase and the corresponding errors between the empirical degradation model and the actual battery system are obtained. The errors are given by:

$$\Delta h_C = h_C - h'_C \tag{11}$$

where Δh_C is the difference between the real battery SOH h_C and empirical degradation model SOH prediction values h'_C in the C cycle.

Step 1: Take n P_{train} and T_{train} to train the BP NN. Here, P_{train} and T_{train} sets are given by:

$$\begin{cases} P_{train} = [I_{in.c}, V_{in.c}, I_{out.c}, V_{out.c}]_{n\times 4} \\ T_{train} = [\Delta h_C]_{n\times 1} \end{cases} \tag{12}$$

where $I_{in.c}$, $V_{in.c}$, $I_{out.c}$, and $V_{out.c}$ are the average charging current, average charging voltage, average discharge current and average discharge voltage in the C charge-discharge cycle, respectively; n is the sum of the charge-discharge cycles for M lithium-ion batteries.

Step 2: Initialize the corresponding parameters of the bp neural network. The number of nodes of the network input layer is determined according to the dimension of the input variable, the dimension of the output variable determines the number of nodes of the output layer, and the number of nodes of the hidden layer is generally obtained by experience; At the same time, the network connection weight, the implicit layer threshold and the output layer threshold are initialized, and the appropriate learning rate and training function are selected.

Step 3: Use the trained BP NN model to calculate the errors between the empirical degradation model and the actual battery by using the actual working condition features $I_{in.c}$, $V_{in.c}$, $I_{out.c}$, and $V_{out.c}$ of the tested battery as model inputs. Based on the calculated errors by the model outputs, correct the prediction results of empirical degradation model to improve the SOH estimation performance.

C. ERROR COMPENSATION MODEL BASED ON DATA-DRIVEN METHOD

1) CONVEX OPTIMIZATION ALGORITHM

Since the battery is a typical dynamic, nonlinear system, its degradation process is affected by many factors. The measured life data have different degrees of noise pollution. If the original data is not denoised, the noise will have a great impact on the estimation of unknown parameters in the empirical degradation model, thus further affecting the accuracy of the prediction results. Convex optimization theory has the characteristics of quickly solving the optimal solution of the problem and provides excellent noise reduction performance in terms of data smoothness. In this paper, a convex optimization algorithm is used to preprocess the measured data of batteries, and then the data after noise reduction are used as the data basis for parameter identification of empirical degradation model.

"Convex optimization" refers to the optimization problem in which the objective function is a convex function, and the constraint variable takes values in a convex set. The convex optimization principle is expressed as follows:

$$\textit{minimize}\ \|\text{Ax-b}\| \tag{13}$$

In Eq. (13), $A \in R^{m\times n}$ and $b \in R^m$ are the data of the problem, $x \in R^n$ is the variable, and $\|\cdot\|$ is a norm on R^m.

Select the quadratic smooth convex function:

$$\phi_{quad}(x) = \sum_{i=1}^{n-1}(x_{i+1} - x_i)^2 = \|Dx\|_2^2 \tag{14}$$

where $D \in R^{(n-1)\times n}$ is a double diagonal matrix.

Add a regularization term related to the degree of smoothness:

$$\textit{minimize}\ \|Ax - b\|_2^2 + \sigma\ \|Dx\|_2^2 \tag{15}$$

where σ is the regularization parameter ($\sigma \geq 0$) and the appropriate regularization parameter is selected based on experience. σ controls the smoothness of the approximation solution, thus obtaining the optimal trade-off between $\|Ax - b\|_2$ and $\|Dx\|_2$, and then the optimal solution is achieved.

2) METHODS

The fusion estimation model consists of an empirical degradation model and an error compensation model. The empirical degradation model is mainly used to describe the overall degradation trend of batteries. Combining with the actual working environment of batteries, the error compensation model supplements the uncertainty and difference in the battery degradation process, which improves the applicability and accuracy of the single model. The flow chart of lithium-ion battery SOH estimation method based on the proposed fusion framework is shown in Fig. 4.

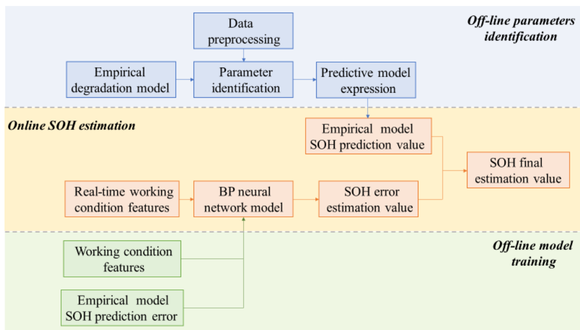

FIGURE 4. **Lithium-ion battery SOH estimation method based on the fusion framework.**

The whole framework can be divided into three parts: off-line parameter identification, offline and online SOH estimation model training.

Firstly, in the off-line parameter identification stage, a set of battery off-line capacity data is selected as the data basis for parameter identification of empirical degradation model. The convex optimization algorithm is used to denoise the historical capacity data of the battery. Based on the smoothed data, the unknown parameters in the empirical degradation model are identified by the least squares algorithm. Based on the results of parameter identification, the specific expression of the empirical degradation model is obtained. The SOH degradation trend of the same type of lithium-ion battery can be predicted based on the model expression. Then, based on the prediction results of the empirical degradation model and the real SOH values of the training set batteries, the SOH prediction value and corresponding SOH prediction error value were obtained.

Secondly, in the off-line model training phase, four different operating states of the first feature are extracted from battery off-line training data. The extracted features of the training input data as a model error compensation and output a corresponding degradation SOH empirical model prediction errors. The corresponding parameters of the bp neural network are initialized. The error compensation model is trained based on bp neural network algorithm.

Finally, in the online SOH estimation process, the four working condition features are extracted firstly from the testing battery during its charging and discharging stage. As the model input, the selected features are directly applied to estimate the error based on the trained BP NN model. The estimated error values are fed back to the predicted results of the empirical degradation model to realize online error compensation.

III. EXPERIMENTS AND ANALYSIS

A. BATTERY DATA SET AND WORKING CONDITION FEATURE EXTRACTION

The lithium-ion battery degradation experiment data involved in this paper come from NASA Ames Prognostics Center of Excellence (PCoE) [35]. The 18650 sized batteries (B5, B6 and B18) were run under 3 different operational profiles (charge, discharge and impedance) at temperature of 24°C. The charging current was constant with a level of 1.5A until the battery voltage reached 4.2V. Then, the batteries were continued in a constant voltage charging mode until the charge current fell to 20mA. For batteries B5, B6 and B18, discharge was run at a constant current level of 2A until the battery voltage dropped to 2.7V, 2.5V and 2.5V respectively. Details of the selected lithium-ion batteries are shown in Table 2. The actual data of the charging-discharging current and voltage in different cycles are monitored and provided by NASA battery data set. During each cycle, the average values of charging-discharging current and voltage are calculated as the working condition features of the current cycle of batteries, which are the average charging current, average charging voltage, average discharge current and average discharge voltage. The four working condition features under different cycles are calculated respectively. The final result is shown in Fig. 5.

TABLE 2. Test lithium-ion batteries information.

Battery ID	Discharge current	Rated capacity	CC/CV	End voltage
B5	2A	2Ahr	1.5A/20mA	2.7V
B6	2A	2Ahr	1.5A/20mA	2.5V
B18	2A	2Ahr	1.5A/20mA	2.5V

As shown in Fig. 5, the charge-discharge process voltage and the average current are not kept constant in the actual system. Due to the influence of inherent battery degradation factors, experimental conditions, working environment etc., the change is accompanied by strong nonlinearity and uncertainty. To verify the association between extracted features and battery health degradation, the Pearson Correlation Coefficient between the four working condition features and capacity of lithium-ion batteries was calculated respectively according to Eq. (10). The results are shown in Table 3.

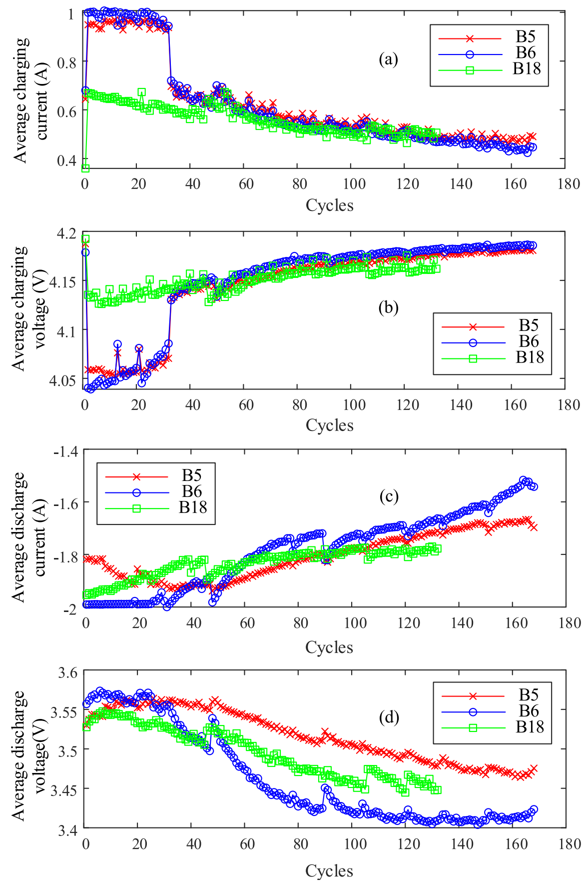

FIGURE 5. Working condition features extraction: (a) average charging current; (b)average charging voltage; (c) average discharge current; (d) average discharge voltage.

TABLE 3. The Pearson Correlation Coefficient between SOH and working condition features.

Number	Average charging voltage	Average charging current	Average discharging voltage	Average discharging current
B5	-0.8156	0.8523	0.9824	-0.9333
B6	-0.8736	0.9149	0.9652	-0.9891
B18	-0.8020	0.8386	0.9856	-0.9660

In Table 3, it can be seen that the absolute value of Pearson's Correlation Coefficient are all greater than 0.8, and the relationship between each feature and battery SOH shows a good correlation, indicating that the selected features contain much information related to battery SOH; In addition, it can be seen in Fig.5 that due to the differences in the inherent degradation characteristics of the battery itself and the actual operating environment, the extracted four working condition features from different batteries are quite varied, which directly leads to different degradation trends for different batteries. In addition, the battery SOH degradation does not presented a simple monotonous degradation trend accompanied by capacity surges and uncertain fluctuations, as shown in Fig. 6.

B. EVALUATION CRITERIA

Three evaluation criteria, mean absolute percentage error (ε_{MAPE}), root mean square error (ε_{RMSE}) and max error

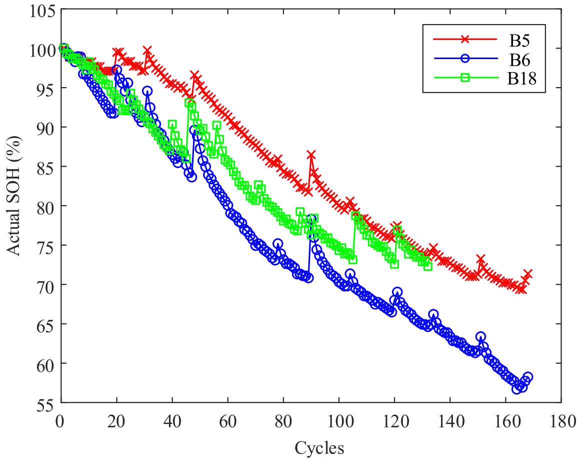

FIGURE 6. Actual SOH distribution.

(ε_{MAX}), are adopted to assess the estimation performance of the proposed methods, defined as Eq. (16), (17) and (18).

$$\varepsilon_{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{h_{tr_i} - h_{pr_i}}{h_{tr_i}}\right| \times 100\% \tag{16}$$

$$\varepsilon_{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{N}(h_{tr_i} - h_{pr_i})^2} \tag{17}$$

$$\varepsilon_{MAX} = \left|h_{tr_i} - h_{pr_i}\right| \tag{18}$$

where h_{tr_i} and h_{pr_i} are the real value and estimation value of battery SOH in the i cycle, $i = 1, 2, \cdots, N$.

C. EXPERIMENTAL RESULTS AND DISCUSSION

Combined with the degradation data of NASA battery data set, the experimental verification and analysis of the proposed method are carried out.

1) EXPERIMENTAL PROCEDURE

According to the SOH estimation process of lithium-ion batteries based on the fusion model, the specific experimental procedure is as follows:

First, the empirical degradation model Mod1 of lithium-ion battery SOH with its charge-discharge cycle is constructed. The battery B5 is selected as the data basis of model parameter identification. The initial capacity is 1.8565Ah. There are 168 sets of lithium-ion battery data in B5, including charge-discharge cycles and AC. The AC data are processed by the convex optimization algorithm to reduce the noise of the original data; unknown parameters of the model are identified based on the preprocessed data, and the value of each parameter and its 95% confidence interval (the test data and the prediction data are normalized) are shown in Table 4.

According to the parameter identification results, the specific expression of the empirical degradation model Mod1 is:

$$h = -0.002259C - 0.04945e^{-0.0465C} + 1.04945 \tag{19}$$

TABLE 4. Parameter identification results and corresponding confidence intervals.

Parameter	Identification value	Confidence interval
α	-0.0465	(-0.05613, 0.03687)
k_1	-0.002259	(-0.002312, 0.002207)
k_2	-0.04945	(-0.002312, 0.002207)

Based on the expression, Fig. 7 shows the empirical degradation model fitting results for battery B5.

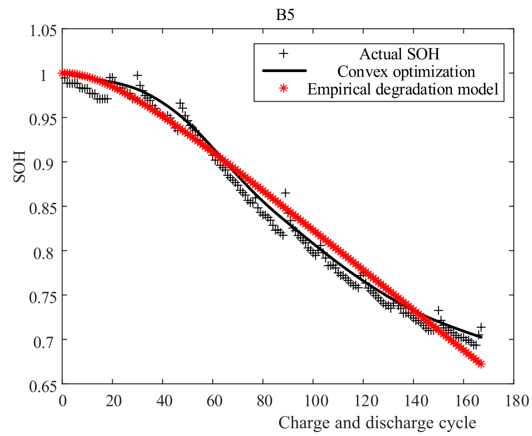

FIGURE 7. Empirical degradation model fitting results for battery B5.

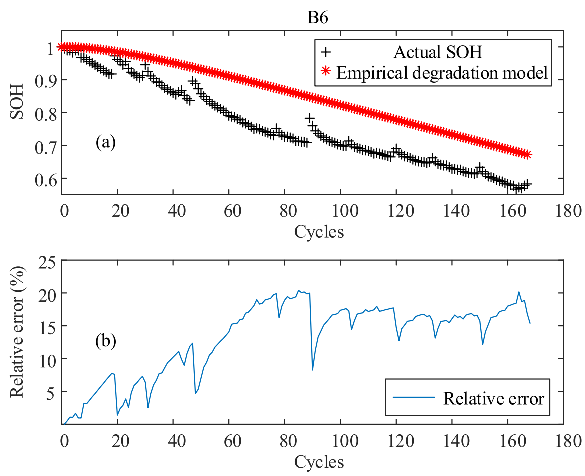

FIGURE 8. Empirical degradation model prediction results for battery B6: (a) SOH prediction results; (b) Relative error percentage distribution.

The empirical degradation model identified by the battery B5 is directly applied to batteries B6 and B18. Fig. 8 and 9 shows the prediction results and the relative error percentage distribution of these two batteries. Based on the prediction results, we can achieve the empirical degradation model prediction error Δh_c according to the Eq. (11).

Fig. 8 and 9 show that the degradation trends of the three batteries are not the same. Because of the difference in inherent degradation characteristics and working environments, even for the same type of batteries, the degradation process also shows great differences. Therefore, the prediction results of the empirical model need to be supplemented by the error compensation model. The BP neural network is taken as the

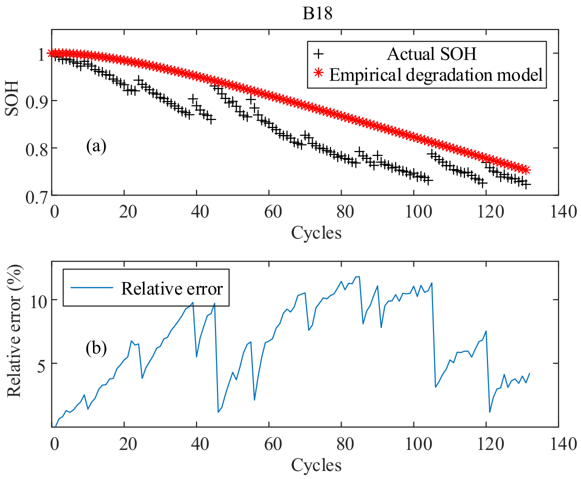

FIGURE 9. Empirical degradation model prediction results for battery B18: (a) SOH prediction results; (b) Relative error percentage distribution.

TABLE 5. Mod2 training set and test set distribution.

Training set	Test set
B5, B6	B18
B5, B18	B6
B5, B18	B5

algorithm basis of the error compensation model Mod2 in this paper. A cross-validation approach was performed based on battery B5, B6 and B18. According to Table 5, the three sets of batteries are divided into training set and test set respectively.

Based on the battery historical degradation data and the empirical degradation model prediction error acquired by Mod1, training input set P_{train} and training output set T_{train} of Mod2 are respectively constructed according to the Eq. (12). The BP NN is trained based on the training set. According to experience, the main parameters setting of BP NN are shown in Table 6.

TABLE 6. Parameters Setting of BP Neural Network.

Parameters	Setting
Neurons in input layer	4
Neurons in output layer	1
Hidden layer numbers	1
Neurons in hidden layer	3
Epochs	1000
Training function	Trained

The working condition features $I_{in.c}$, $V_{in.c}$, $I_{out.c}$, and $V_{out.c}$ of test set battery are respectively brought into the trained Mod2, and the model output is the empirical degradation model error prediction value; the error prediction value is fed back to the prediction results of the empirical degradation model Mod1.The final estimation results are shown in Fig. 10, 11 and 12 for battery B5, B6 and B18, respectively.

2) DISCUSSION AND COMPARISON

The ε_{MAPE}, ε_{RMSE} and ε_{MAX} are calculated separately according to Eq. (16), (17) and (18), and the performance

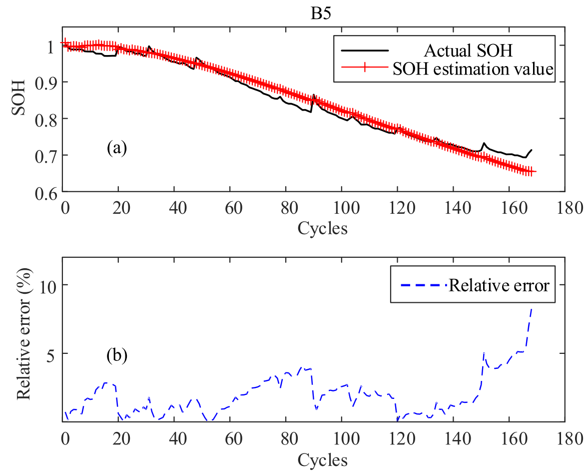

FIGURE 10. Fusion model estimation results for battery B5: (a) SOH estimation results; (b) Relative error percentage distribution.

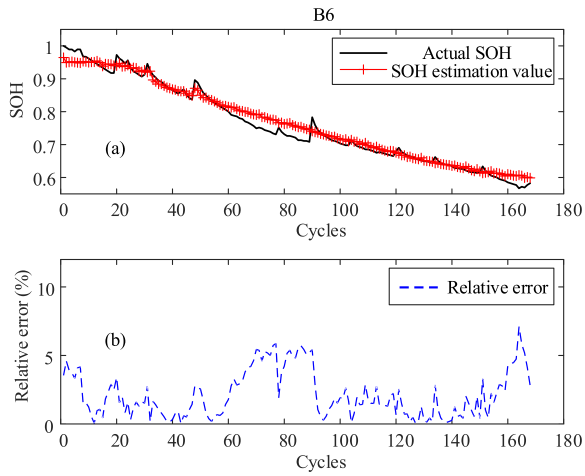

FIGURE 11. Fusion model estimation results for battery B6: (a) SOH estimation results; (b) Relative error percentage distribution.

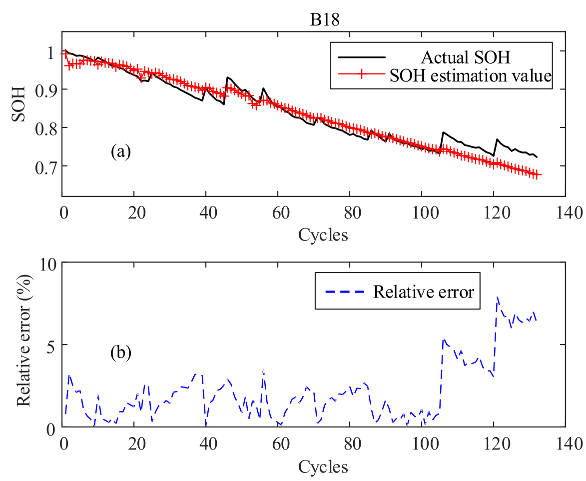

FIGURE 12. Fusion model estimation results for battery B18: (a) SOH estimation results; (b) Relative error percentage distribution.

comparison between the empirical degradation model and the fusion estimation model is shown in Table 7.

Based on the above results, the following conclusions can be drawn:

TABLE 7. Performance and comparison.

Model	Evaluation Criteria	B5	B6	B18
Empirical model	$\varepsilon_{MAPE}(\%)$	-	13.2005	6.5382
	$\varepsilon_{RMSE}(\%)$	-	0.1005	0.0589
	$\varepsilon_{MAX}(\%)$	-	0.1455	0.0908
Fusion model	$\varepsilon_{MAPE}(\%)$	1.9447	2.1475	2.2171
	$\varepsilon_{RMSE}(\%)$	0.0191	0.0205	0.0227
	$\varepsilon_{MAX}(\%)$	0.0588	0.0457	0.0608
LSTM[36]	$\varepsilon_{RMSE}(\%)$	0.044	0.055	0.026
CNN[37]	$\varepsilon_{RMSE}(\%)$	0.020	0.023	0.022

First, as seen from Figs. 10-12, the relative error of the fusion model is mostly less than 5%, which indicates that the proposed fusion estimation framework can effectively estimate the SOH of batteries. In addition, for the same battery, the comparison results of the three methods given in Table 7 show that the performance of the fusion model is better than the empirical degradation model, LSTM and CNN. Compared with these three methods, the performance of SOH estimation is greatly improved, indicating that error compensation is effectively realized. The estimation accuracy is fundamentally improved, and the applicability of the empirical model on different batteries is greatly improved. Estimation accuracy is fundamentally increased, and the applicability of empirical models on different batteries is improved greatly. The fusion framework can extract the working condition features of batteries from the actual environments, effectively considering the impact of the actual internal and external environments on their degradation, and improve the adaptability of the model. Compared with the existing methods, this method can not only evaluate the full-life cycle SOH of lithium-ion batteries, but also evaluate the health status of different batteries of the same type.

IV. CONCLUSION

This paper proposes a prediction framework based on the fusion of empirical degradation models and data-driven methods to solve the problems of lithium-ion battery health estimation and remaining life prediction, and experimentally validates and evaluates the proposed method based on NASA PCoE battery test data. The work of this paper has two main aspects: first, an empirical degradation model of lithium-ion battery capacity is established; secondly, the actual information of four operating conditions is extracted from the charging and discharging conditions of the lithium-ion battery, and an error compensation model based on a data-driven method is established to describe the difference in operating conditions The impact of battery performance on battery degradation improves the accuracy of SOH estimation during battery degradation. The main research contents of this article are as follows:

1) The life degradation process of lithium-ion batteries is analyzed, the battery capacity empirical degradation model is proposed from the perspective of the degradation rate, and the remaining life prediction methods of lithium-ion batteries are studied based on the empirical degradation model. Under standard operating conditions, the model is universal. As long as the initial capacity is known, the battery life curve can be directly simulated, which has good practicability and indicates the limitations of the model.

2) Because the prediction method based on the empirical degradation model is too dependent on the model and has poor individual adaptability, the framework of the SOH estimation method based on the fusion of the empirical degradation model and the data-driven method is proposed. The verification results using NASA PCoE battery test data show that for different batteries, the mean absolute percentage error of the three batteries is approximately 2%, root mean square error is approximately 0.02, and the max error is no more than 0.1, while the prediction performance of the empirical model on different batteries is not very well, which is mainly due to the difference in the inherent degradation characteristics of batteries and actual operating environments. The proposed fusion method can describe the impact of actual operating conditions on battery degradation well and can effectively improve the accuracy of battery SOH estimation.

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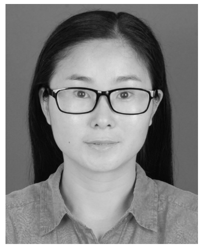

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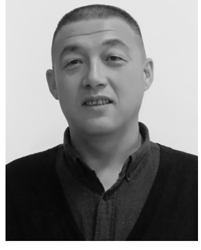

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