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Lithium-ion Battery Remaining Useful Life Prediction Based on Exponential Smoothing and Particle Filter

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To more accurately predict the remaining useful life of batteries, in this paper, a novel hybrid method that includes a particle filter, exponential smoothing and a capacity degradation model is proposed. First, the parameters of the dynamic model of a lithium-ion battery are estimated by the particle filter to acquire the parameters at each cycle in the estimation phase. Second, these parameters are processed and weighted by exponential smoothing to export the weighted averages of these parameters as the predictive parameters. Finally, the predictive parameters are brought into an empirical capacity degradation model to predict the remaining useful life of the lithium-ion battery. The comparative experiments for predicting the remaining useful life with different end-of-monitoring thresholds are performed to verify the higher accuracy and stability of this hybrid method compared to the pure particle filter method.

Keywords: Lithium-ion battery, Remaining useful life, Exponential smoothing, Particle filter, Parameter estimation.

1. INTRODUCTION

Compared with lead-acid batteries, nickel-cadmium batteries or nickel-metal hydride batteries, lithium-ion batteries have the advantages of a higher energy density, lower self-discharge rate, longer lifetime and no memory effect [1], and they have been widely used in electronic products, such as mobile phones and laptops, hybrid/pure electric vehicles, the aerospace industry and other fields. The degradation of lithium-ion batteries affects the safety of electrical equipment [2], so a method that can monitor the state-of-health (SOH) and predict the remaining useful life (RUL) of the battery accurately and rapidly is needed to better determine the working condition and safety of batteries. Battery degra-

dation occurs in many aspects [3], such as the decline of capacity, current, voltage and instantaneous power and the increase of impedance and the self-discharge rate. Usually, capacity and impedance are selected as the evaluation indicators of battery degradation [4]. Based on previous studies, methods for battery prognostics can be roughly divided into three categories: data-driven methods, model-based methods, and hybrid methods.

Simply speaking, data-driven methods tend to analyse historical data to excavate potential rules and then apply these rules to predict the development of events [5]. Therefore, it is not necessary to have a profound knowledge of the degradation mechanism of a battery. The degradation law of the battery can be predicted simply by rules derived from historical data, and the advantages of such methods are now apparent. Chao Hu et al. [6] proposed an integrated data-driven method that contained multiple seed algorithms and integrated them with a weight strategy based on accuracy, diversity and optima; this method showed high accuracy and robustness for RUL prediction. Patil et al. [7] proposed a multi-node support vector machine method that combined a classical model and a regression model to improve prediction accuracy, and with the benefits of multi-node computing, this method improved program efficiency and resulted in a well-trained model with the possibility of real-time online RUL prediction. The disadvantages of data-driven methods are also obvious. On one hand, the accuracy and robustness of predicted results will be greatly reduced when historical data is insufficient or unreliable; on the other hand, the timeliness of prediction results will be seriously reduced by the calculational complexity of intelligent algorithms [8].

Contrary to data-driven methods, model-based methods require analysis of the degradation mechanism of lithium-ion batteries and depend less on historical data. The electrochemical model, equivalent circuit model, and empirical model are commonly used in current research [9]. The electrochemical model is composed of three processes: mass transfer, electric conduction and electrochemical reaction [10]. These three processes are organically unified by governing equations. The equivalent circuit model does not require an in-depth analysis of the electrochemical reaction inside the battery; rather, this model uses descriptions of the open-circuit voltage, DC internal resistance and polarisation internal resistance in the circuit to express the external characteristics of the battery [11]. The empirical model represents a mathematical relationship between the inputs and outputs, which means the data obtained from the actual process is analysed by mathematical statistics, and the relations between the inputs and outputs are determined according to the principle of minimum error [12]. Compared with the other two models, empirical models are more easily applied to online prediction, so they are the most widely selected type of method in the study of battery RUL prediction, and models such as the exponential increase model based on impedance, the exponential decrease model based on capacity, the polynomial model, the Kalman filter and the particle filter are often used to estimate the parameters and states of empirical models [13]. The model-based methods consist of two phases: an estimation phase and a prognostics phase. Due to the lack of measurements, the model parameters will not be updated in the prognostics phase [14], which means the last parameters in the estimation phase will be applied to predict the RUL, potentially leading to large errors.

The data-driven methods and model-based methods have their own advantages and limitations, so more research should be concentrated on combining them to develop their abilities to achieve higher performance than a single method. Dong Wang et al. [15] proposed a hybrid method that contained a

relevance vector machine (RVM) and a capacity degradation model to predict the RUL of lithium-ion batteries. Representative training vectors, including the cycle of relevance vectors and the predicted value at this cycle, were determined by the RVM. The predicted values at each cycle were fitted by the capacity degradation model, and the RUL value was calculated by an extrapolation method. Yang Chang et al. [16] proposed a hybrid method based on error correction. First, the predicted result and a raw error series were obtained by an unscented Kalman filter, then the complete ensemble empirical mode decomposition was adopted to construct a new error series, and finally, the new error series was utilised by an RVM to correct the predicted result. The hybrid method utilises both the stability of the model and the creativity of big data, which can improve prognostic performance to some extent.

Inspired by the limitations of the model-based methods mentioned above, this paper proposes a novel hybrid method composed of a particle filter (PF), exponential smoothing (ES) and an empirical capacity degradation model to predict the RUL of a lithium-ion battery. Implementation of the proposed method can be divided into three phases: in the start-up phase, the parameters of the dynamic lithium-ion battery model are estimated using the PF algorithm, and the parameters at each estimation cycle are acquired; in the following phase, the parameters acquired by the PF are processed and weighted by the ES algorithm, and the weighted averages of these parameters are exported as the predictive parameters; in the last phase, the predictive parameters are brought into the empirical capacity degradation model to predict the remaining useful life of the lithium-ion battery. Comparative RUL prediction experiments with different end-of-monitoring thresholds are conducted, and the results show that the proposed ES-PF hybrid method can achieve more accurate and stable prognostic results compared with the PF method. Benefiting from the iterative nature of the ES algorithm, the computation speed does not decline substantially.

The remaining sections of this paper are arranged as follows. The theories and concepts related to particle filters and exponential smoothing algorithms are explained in section 2. Section 3 provides cycle life experiments and the capacity degradation model of a lithium-ion battery. Section 4 conducts prediction experiments of the RUL of a lithium-ion battery. Section 5 presents three evaluation indicators and analyses the predicted results of battery RUL based on these indicators. The conclusions are discussed in section 6.

2. PARTICLE FILTER AND EXPONENTIAL SMOOTHING

The particle filter is a method to solve the integral problem of Bayesian optimal estimation with the concept of the Monte Carlo integral [17]. It is the process of searching a group of random samples that propagate in the state space, then regarding these samples as the posterior probability density function of the system and substituting the average of these samples for the integral in the Bayesian optimal estimation. These samples are known figuratively as "particles". The particle filter removes the constraint condition of the Kalman filter that the random variables must satisfy the Gaussian distribution and solves the problem of particle degeneracy to some extent [18]. To better understand the proposed method, it is necessary to first explain the standard particle filter algorithm.

2.1 Particle filter algorithm

Consider the state transition function and measurement function of the dynamical system model as [19]

$$x_k = f_k(x_{k-1}, \omega_{k-1}) \quad (1)$$

$$z_k = h_k(x_k, v_k) \quad (2)$$

Here, x_k represents the system state at time k, f_k represents the state transition function of state x_{k-1}, ω_{k-1} is the process noise at time $k-1$, h_k is the measurement function of state x_k, v_k represents the measurement noise at time k, and z_k is the measured value at time k.

The process of the particle filter algorithm is as follows.

(a) Set the algorithm parameters.

The number of particles N, the covariance of the process noises P_k and the measurement noises R_k, and the driving transaction matrix are included.

(b) Initialise the particle set.

The initial states of each particle x_0^i are obtained by sampling from the initial distribution $p(x_0)$. Each particle is assigned a weight w_k^i, and $\{x_k^i, w_k^i\}$ is used to present the state and weight of the ith particle at time k. At this step, the weights of all the particles are equal, as represented by $\{x_0^i, 1/N\}$.

(c) Importance sampling.

It is the best choice to sample from the posteriori distribution of the system $p(x_{0:k}|z_{1:k})$, but $p(x_{0:k}|z_{1:k})$ is multivariable and nonstandard, which makes it difficult to sample from directly [20]. Usually, a known probability density distribution $q(x_{0:k}|z_{1:k})$, which is easy to sample from, is introduced, and this distribution is called the importance distribution [21].

(d) Calculate the importance weights.

z_k is needed at this step, and the original formula of weight calculation is represented as

$$w_k(x_{0:k}) = \frac{p(z_{1:k}|x_{0:k})p(x_{0:k})}{q(x_{0:k}|z_{1:k})} \quad (3)$$

Here, $w_k(x_{0:k})$ is the unnormalised importance weight, $p(z_{1:k}|x_{0:k})$ is the likelihood function, and $p(x_{0:k})$ is the prior distribution. Formula (3) is not recursive, so it is not suitable for computer programming.

Suppose that the current state is independent of future measurements; then, the importance function can be written in the form of continuous multiplication as follows.

$$q(x_{0:k}|z_{1:k}) = q(x_0)\prod_{j=1}^{k} q\left(x_j|x_{0:j-1}, z_{1:j}\right) \quad (4)$$

Assume that the state variables conform to the first-order Markov process. Then,

$$p(x_{0:k}) = p(x_0)\prod_{j=1}^{k} p\left(x_j|x_{j-1}\right) \quad (5)$$

$$p(z_{1:k}|x_{0:k}) = \prod_{j=1}^{k} p(z_j|x_j) \quad (6)$$

Equations (4-6) are brought into formula (3) to obtain the recurrence formula of the weights [22].

$$w_k = w_{k-1}\frac{p(z_k|x_k)p(x_k|x_{k-1})}{q(x_k|x_{0:k-1},z_{1:k})} \tag{7}$$

If the prior distribution $p(x_k|x_{k-1})$ is chosen as the importance distribution, i.e.,

$$q(x_k|x_{0:k-1},z_{1:k}) = p(x_k|x_{k-1}) \tag{8}$$

then the recurrence formula can be written as the product of the weight at the previous moment and the likelihood function [23].

$$w_k = w_{k-1}p(z_k|x_k) \tag{9}$$

The importance weights are normalised using the following formula.

$$w_k^i = \frac{w_k^i}{\sum_{j=1}^{N} w_k^j} \tag{10}$$

(e) Re-sampling.

Particle degeneracy will reduce the diversity of the particles [18]. The re-sampling technique can solve the problem by reproducing and abandoning the particles $\{x_k^i\}_{i=1}^N$ according to their weights [24]. To elaborate, the particles with large weights will be vastly reproduced, and the particles with weights close to zero will be reduced or abandoned. The weights of all particles will return to $1/N$ after re-sampling.

(f) Estimation.

Regard the mathematical expectation of the particle distribution as the estimated value.

$$\tilde{x}_k = \sum_{i=1}^{N} w_k^i x_k^i \tag{11}$$

(g) Circulation.

If $k \le T$ (where T is the last number of measurements), let $k = k + 1$, and turn to step c; else, stop the algorithm.

From the above algorithm process, in the estimation phase of battery RUL prediction, the parameters of the model remain updated because of the continuous supply of measurements. However, there is no measurement in the prognostics phase, and the parameters will retain their values from the last estimated cycle. Then, the parameters in this cycle are used in the model to predict the RUL without utilising the change rules of the parameters hidden in the historical data. The proposed method is exactly inspired by this problem.

2.2 Exponential smoothing algorithm

Exponential smoothing is a prediction method commonly used in management science [25]. It smooths historical data to obtain reasonable predicted values.

Suppose the time series to be $x_1, x_2, \ldots, x_k$.

$$S_k = \frac{x_k + x_{k-1} + \cdots + x_{k-N+1}}{N}, k \ge N \tag{12}$$

Then, the exponential smoothing formula is as follows.

$$S_k = \alpha x_k + (1-\alpha)S_{k-1} \tag{13}$$

Here, S_k represents the exponential smoothing result. α is the weighting coefficient, and $0 < \alpha < 1$.

Expand formula (13) successively.

$$\begin{aligned} S_k &= \alpha x_k + (1-\alpha)[\alpha x_{k-1} + (1-\alpha)S_{k-2}] \\ &= \alpha x_k + \alpha(1-\alpha)x_{k-1} + (1-\alpha)^2 S_{k-2} \\ &= \cdots \\ &= \alpha x_k + \alpha(1-\alpha)x_{k-1} + \alpha(1-\alpha)^2 x_{k-2} + \cdots + (1-\alpha)^k S_0 \\ &= \alpha \sum_{j=0}^{k-1} (1-\alpha)^j x_{k-j} + (1-\alpha)^k S_0 \end{aligned} \quad (14)$$

When k tends to infinity, $(1-\alpha)^k$ tends to zero, so equation (14) is simplified to equation (15).

$$S_k = \alpha \sum_{j=0}^{\infty} (1-\alpha)^j x_{k-j} \quad (15)$$

From equation (15), S_k is the weighted average of $x_k, x_{k-1}, \ldots, x_{k-j}, \ldots$. The weighting coefficients are $\alpha, \alpha(1-\alpha), \alpha(1-\alpha)^2, \ldots$ respectively, and the closer the data is, the more weight it has, and vice versa, and the sum of the weights is one.

Consider S_k as the predicted value at time $k+1$. The prediction model can be shown as follows.

$$\hat{x}_{k+1} = \alpha x_k + (1-\alpha)\hat{x}_k \quad (16)$$

Expand equation (16) and rewrite it as follows.

$$\hat{x}_{k+1} = \hat{x}_k + \alpha(x_k - \hat{x}_k) \quad (17)$$

From equation (17), the new predicted value is obtained by modifying the former predicted value according to the prediction error. The size of α embodies the size of the correction range: the larger the α, the greater the correction range, and vice versa. The value of α not only affects the response speed of the prediction model but also determines the ability of the prediction model to correct for errors. There is perceptual knowledge for the selection of α:

(1) if the time series is smooth and steady, the value of α should be small to narrow the correction range and to make the prediction model contain longer time series information;

(2) if the time series fluctuates quickly and obviously, the value of α should be large to improve the sensitivity of the prediction model and to rapidly keep up with data changes.

In practice, several values of α are used for trial calculations, and then one of the values that yields the smallest prediction error is selected as the model weighting coefficient.

In this paper, the exponential smoothing algorithm is used to process the historical data of the battery model parameters obtained by the particle filter and to acquire reasonable predicted parameters of the battery degradation model, which is required in the prognostics phase. The flow chart of the proposed ES-PF algorithm is shown in Fig. 1. Here, EOM represents the end of the monitoring, k_{EOM} represents the cycle number at the end of the monitoring, EOL represents the end of life of the batteries, and k_{EOL} represents the cycle number at the end of life of the batteries.

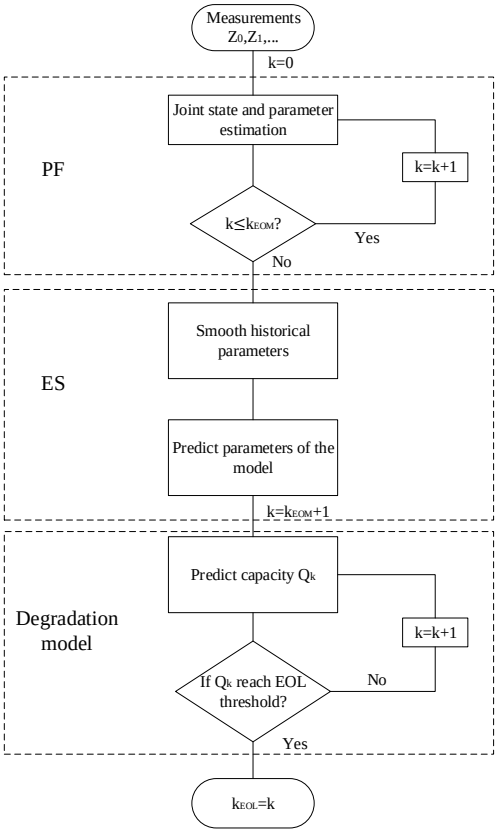


Figure 1. Flowchart of the proposed hybrid method.

3. EXPERIMENT AND BATTERY DEGRADATION

3.1 Battery cycle life experiments

Lithium-ion battery cycle life experiments were conducted first to obtain the data, which are used to estimate the parameters and demonstrate the validity of the proposed method.

The rated capacity of the 18650 ternary lithium batteries used in the experiments is 1600 mAh, and the nominal voltage, lower cut-off voltage and upper cut-off voltage are 3.7 V, 2.75 V, and 4.2 V, respectively. The experiments were conducted under room temperature (30℃), and two batteries were tested in total. The specific experimental steps are as follows.

(1) Discharge the new batteries in a constant current at 1 C until the battery voltages fall to 2.75 V, and then shelve them for 10 minutes. (The purpose of this step is to discharge the residual capacity in the new batteries.)

(2) Charge the batteries in a constant current at 1 C until the battery voltages reach 4.2 V.

(3) Charge the batteries in a constant voltage at 4.2 V until the current falls to 20 mA, and then shelve them for 30 minutes.

(4) Discharge the batteries in a constant current at 1 C until the voltages fall to 2.4 V and 2.5 V. Then, shelve them for 30 minutes.

(5) Repeat step 2 to step 4 until the actual maximum capacity of the batteries drops to 75% of the rated capacity.

We set up the experimental conditions of overcharge and over-discharge to accelerate the failure of the batteries and to shorten the experimental period. Fig. 2. shows the degradation curves of the battery discharge capacity. The capacity degradation curves of the batteries are different because of the difference of the lower cut-off voltages.

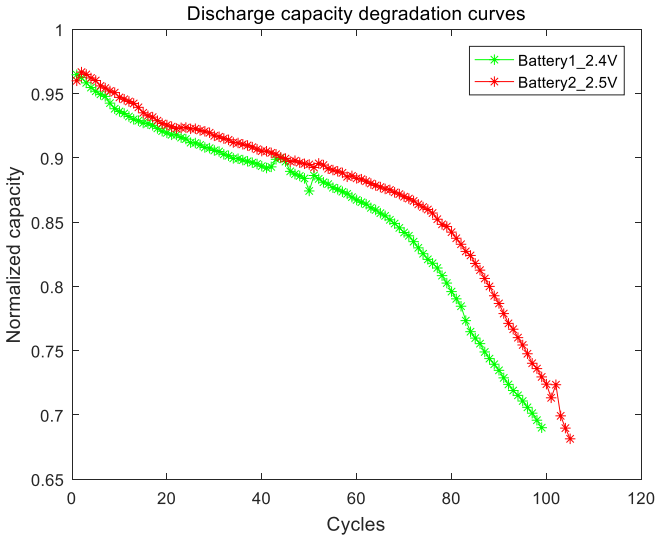


Figure 2. Discharge capacity degradation curves

3.2 Empirical capacity degradation model of lithium-ion battery

Establishing the degradation model of lithium-ion batteries is an important part of remaining us eful life prediction. The electrochemical model has been established according to the electrochemical p rocess inside the battery [26]. Therefore, it is a quite accurate battery model, especially in complex and changeable conditions. However, the establishment of the model is very difficult and requires a thorou gh understanding of the degradation mechanism of batteries [27]. The equivalent circuit model describ es the external characteristics of the battery by describing the open-circuit voltage, DC internal resistan ce and polarisation internal resistance of the battery [28]. However, it cannot directly reflect the capacit y degradation characteristics of batteries. Compared with the two models mentioned above, the empiric al model is commonly used in research. R.B. Wright et al. [29] proposed an empirical model based on i mpedance increases.

$$R(t,T,SOC,\Delta\%SOC) = A(T,SOC,\Delta\%SOC)t^{1/2} + B(T,SOC,\Delta\%SOC) \quad (18-1)$$

$$\begin{cases} A = a(SOC,\Delta\%SOC)\left\{\exp\left[\dfrac{b(SOC,\Delta\%SOC)}{T}\right]\right\} \\ B = c(SOC,\Delta\%SOC)\left\{\exp\left[\dfrac{d(SOC,\Delta\%SOC)}{T}\right]\right\} \end{cases} \quad (18-2)$$

Usually, the accuracy and complexity of a model will increase as the number of parameters incr eases. In addition to the conventional parameters, the model also takes into account the effects of temp erature and state-of-charge, so the accuracy is high and the computation is complicated.

The battery capacity decreases as the number of charge and discharge cycles increases. Saha et al. [30] found that the capacity of lithium-ion batteries decays exponentially, and He et al. [31] proposed an exponential growth model to fit the degradation curve.

$$Q_k = a \times \exp(b \times k) + c \times \exp(d \times k) \quad (19)$$

Here, Q_k represents the capacity at the kth cycle, a, b, c, d represent parameters of the model, and k is a variable of the model that represents the number of cycles. In practice, the parameters of the model vary with time. These four parameters are taken as the states of the model, and the state transition equation and measurement equation can be shown as follows.

$$X(k) = [a(k) \quad b(k) \quad c(k) \quad d(k)]^T \quad (20-1)$$

$$\begin{cases} a(k) = a(k-1) + \omega_a(k) \\ b(k) = b(k-1) + \omega_b(k) \\ c(k) = c(k-1) + \omega_c(k) \\ d(k) = d(k-1) + \omega_d(k) \end{cases} \quad (20-2)$$

$$Q(k) = a(k) \times \exp(b(k) \times k) + c(k) \times \exp(d(k) \times k) + v(k) \quad (21)$$

Here, $X(k)$ is the state vector at the kth cycle, $a(k)$, $b(k)$, $c(k)$, and $d(k)$ are the parameters of the model at the kth cycle, $\omega_a(k)$, $\omega_b(k)$, $\omega_c(k)$, and $\omega_d(k)$ are the process noises at the kth cycle, $v(k)$ is the measurement noise at the kth cycle, and $Q(k)$ is the measurement at the kth cycle.

This model is simpler than the impedance increase model, but its accuracy is also sufficient. To simplify the parameters, Zhang et al. [32] expanded one of the indices by the Taylor formula and obtained a simplified model.

$$Q = a \times \exp(b \times k) + c \times k^g \quad (22)$$

Here, g is an integer variable determined by the degradation rate of batteries based on experience.

Compared with the original model, it reduces one parameter but adds another variable, and its accuracy has not been improved. Considered comprehensively, the double exponential capacity degradation model is the best choice.

4. REMAINING USEFUL LIFE PREDICTION

4.1 Preparatory work

Remaining useful life is defined as the number of cycles from the current cycle to the EOL threshold [14]. The EOL threshold in this paper is 75% of the rated capacity. The RUL of the battery can be calculated using equation (23).

$$RUL = k_{EOL} - k_{EOM} \quad (23)$$

Here, RUL is the cycle number of the remaining useful life of the battery.

The initial values of the model parameters are obtained by fitting the degradation data of battery1 and 2 that were used in the estimation phase and then regarding the averages of the fitting parameters as the initial values of battery2. The results are shown in Table I.

Table 1. The initial values of the model parameters

Battery ID	a	b	c	d
Battery1	-0.0016930	0.04707	0.9505	-0.001096
Battery2	-0.0002283	0.06325	0.9557	-0.001148
Average	-0.0009607	0.05516	0.9531	-0.001122

4.2 RUL prediction

Battery2 is considered as the prediction object, and battery1 just helps to provide the initial parameters. Three EOM thresholds are set to be the 40th, 50th, and 60th cycle, respectively. When $k_{EOM} = 40$, the actual values and the predicted values of $a(k)$, $b(k)$, $c(k)$, and $d(k)$ provided by the proposed method are shown in Fig. 3. The red solid lines represent the value of each parameter predicted by the particle filter in the estimation phase, and the black solid lines are the corresponding actual values. As seen from Fig. 3, the predicted values are very close to the actual values.

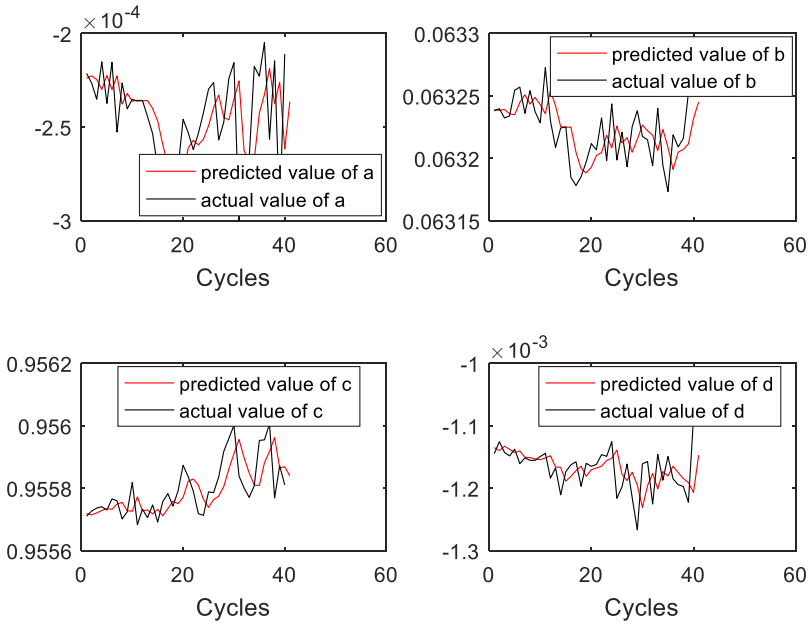


Figure 3. Variation curves of parameters a, b, c, d.

Fig. 4 shows the RUL prediction results under the corresponding EOM thresholds provided by the standard PF method and the proposed method in this paper.

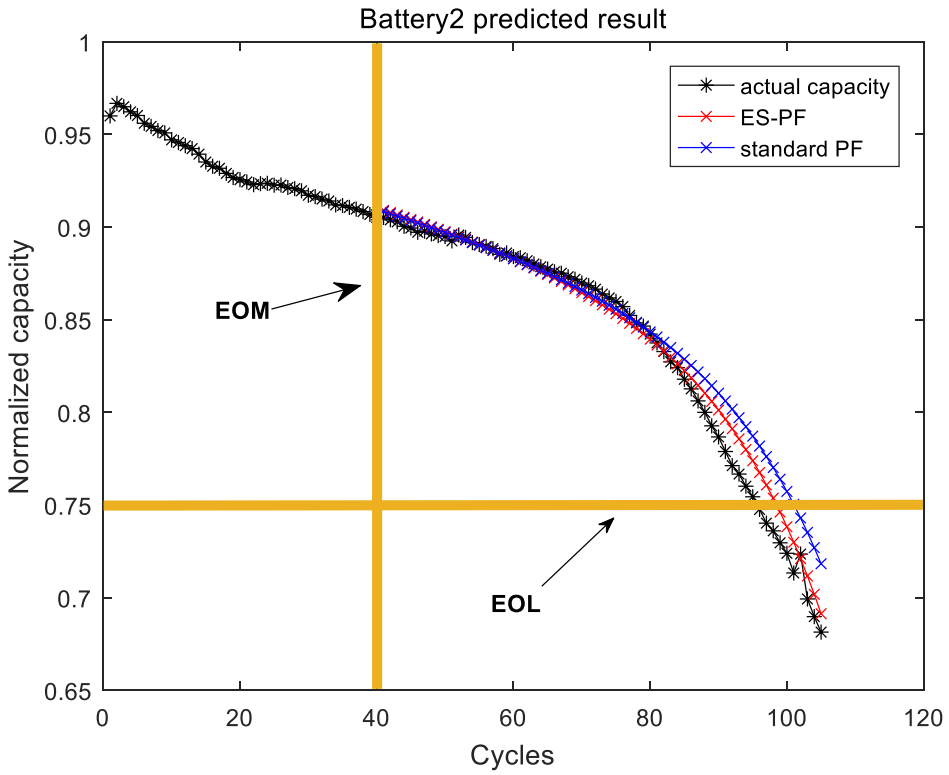
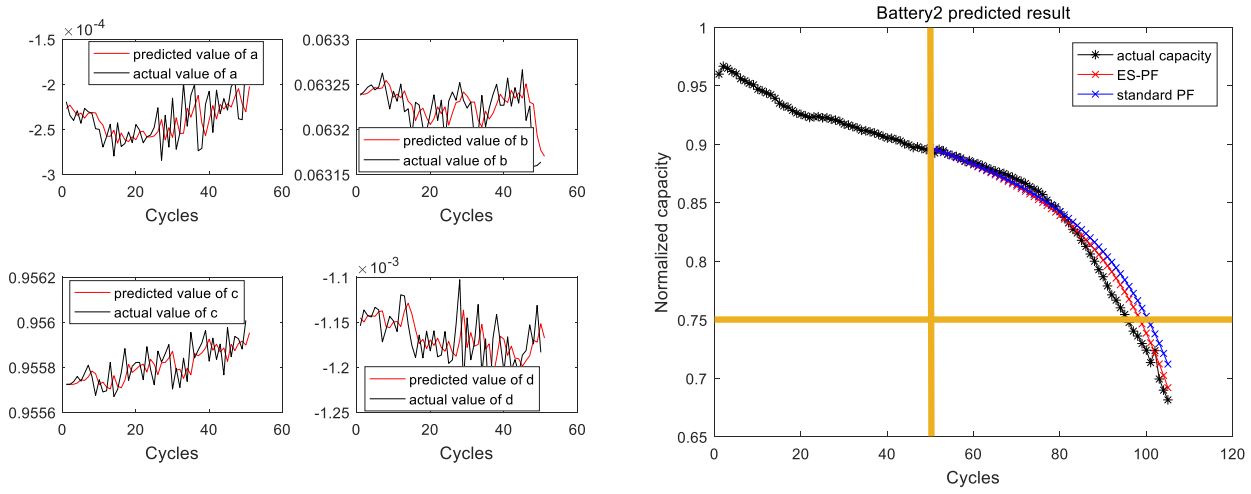


Figure 4. Prediction result of battery2 ($k_{EOM} = 40$).

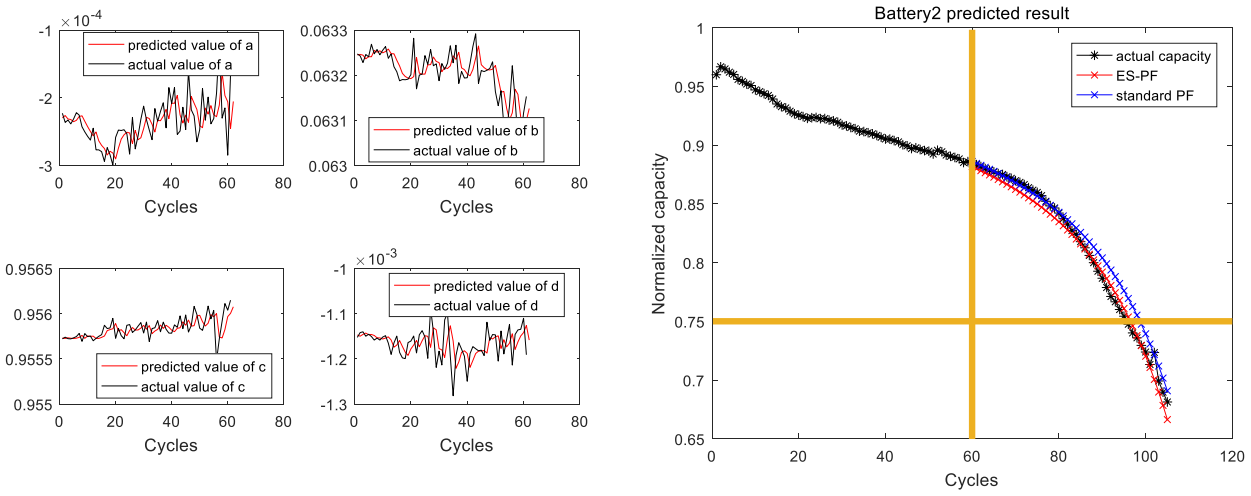
When $k_{EOM} = 50$, the actual values and the predicted values of $a(k)$, $b(k)$, $c(k)$, and $d(k)$ are shown in Fig. 5 (a). Fig. 5 (b) is the RUL prediction result under this EOM threshold.



(a) (b)

Figure 5. (a) Variation curves of parameters a, b, c, d, (b) prediction result of battery2 ($k_{EOM} = 50$).

When $k_{EOM} = 60$, the actual values and the predicted values $a(k)$, $b(k)$, $c(k)$, and $d(k)$ are shown in Fig. 6 (a). The corresponding RUL prediction result is shown in Fig. 6 (b).



(a) (b)

Figure 6. (a) Variation curves of parameters a, b, c, d, (b) prediction result of battery2 ($k_{EOM} = 60$).

5. ANALYSIS OF PROGNOSTIC RESULTS

5.1 Evaluation indicators

Three indicators are chosen to evaluate the predicted results comprehensively [16].

(1) Absolute error (AE)

The raw error between the actual RUL value and the predicted value can be reflected by the absolute error.

$$AE = |RUL_{pre} - RUL_{act}| \tag{24}$$

Here, RUL_{pre} represents the cycle number of the predicted RUL, and RUL_{act} is the cycle number of the actual RUL.

(2) Relative error (RE)

The confidence level of the result is revealed by the relative error. A smaller relative error reflects a higher confidence level, and vice versa.

$$RE = \frac{|RUL_{pre} - RUL_{act}|}{RUL_{act}} \times 100\% \tag{25}$$

(3) Stability error (SE)

The formula of the root mean square error is applied to calculate the stability error, which reflects the stability of the predicted results. A smaller stability error reveals higher robustness of the prediction method, and vice versa.

$$SE = \sqrt{\frac{1}{k_{EOL} - k_{EOM}} \sum_{k=k_{EOM}}^{k_{EOL}} (Q_k - \hat{Q}_k)^2} \tag{26}$$

Here, Q_k represents the actual capacity at the kth cycle, and $\hat{Q}_k$ is the predicted capacity at the kth cycle.

5.2 Result analysis

Table II gives the predicted results and the evaluation indicators of battery2 under three different EOM thresholds using the standard PF method and the proposed ES-PF method.

Table II. Prediction results and evaluation indicators of two methods for battery2.

Group	Method	k_{EOM}	RUL_{act}	RUL_{pre}	AE	RE	SE
1	PF	40	56	62	6	10.71%	0.0150
	ES-PF	40	56	60	4	7.14%	0.0095
2	PF	50	46	51	5	10.87%	0.0121
	ES-PF	50	46	49	3	6.52%	0.0085
3	PF	60	36	39	3	8.33%	0.0090
	ES-PF	60	36	37	1	2.78%	0.0056

From group 1 to group 3 in Table II, the accuracy of the predicted results increases with the value of k_{EOM} regardless of whether the PF method or the ES-PF method is used. This may be because more and more historical measurements are available as k_{EOM} increases, and more reasonable parameters can be provided to the model by learning these historical data. Or it may be that the prediction range will decrease when the EOM threshold moves backwards, reducing the uncertainty of prediction.

From Table II, the proposed ES-PF method has higher accuracy and robustness than the standard PF method under the same conditions. The ES-PF algorithm makes full use of the historical parameters obtained in the estimation phase, and the weights and averages of these parameters are used to provide model parameters that are more reliable than those provided by the standard PF method.

The lower cut-off voltages in the experiments were set below the standard value. The result shows that the cycle life of the batteries is shorter than that of batteries in normal use (the standard cycle life provided by the manufacturer is 300 cycles), and therefore, over-discharge has a great influence on the battery life.

From the above analysis, the conclusions can be summarised as follows: (a) the accuracy of the predicted results increases as the value of k_{EOM} increases regardless of whether the PF method or the ES-PF method is used; (b) the proposed ES-PF method has a higher accuracy and robustness than the standard PF method under the same conditions; and (c) the operation conditions have a certain impact on the cycle life of lithium-ion batteries.

6. CONCLUSIONS

This paper proposes a novel hybrid method, which consists of a particle filter (PF), exponential smoothing (ES) and an empirical capacity degradation model, that can utilise historical parameters obtained in the estimation phase to sufficiently predict the RUL of lithium-ion batteries. The method can be divided into three phases: in the first phase, the parameters of the dynamic lithium-ion battery model are estimated by the PF algorithm, and the parameters in each estimation cycle are acquired; in the second phase, the parameters acquired by the PF are weighted and averaged by the ES algorithm, and then the weighted averages of these parameters are exported as the predictive parameters; in the final phase, the predictive parameters are brought into the empirical capacity degradation model to predict the remaining useful life of a lithium-ion battery. This hybrid method is interdisciplinary because particle filters are used in engineering while exponential smoothing is usually used in management science.

The standard PF method and the proposed method are compared in RUL prediction experiments with lithium-ion batteries. The experiments are divided into three groups with different EOM thresholds, and the results show that the accuracy of prediction is affected by the amount of historical data. However, the proposed method can achieve more accurate and stable results, which verifies the effectiveness and higher performance of the proposed method compared to the standard PF method.

Unlike with experimental conditions, the actual operation conditions of batteries are complex, particularly for power batteries in electric vehicles, which often work in poor conditions with frequent acceleration and deceleration. Therefore, future work should focus on improving the adaptability of the model and considering RUL prediction under multiple operation conditions.

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