A novel intelligent SOC prediction method of lithium-ion battery packs based on the improved unscented transformation

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Abstract. The development of power lithium-ion battery packs is limited by the research and development level of Battery Management System (BMS). In this paper, an improved unscented transformation method is proposed, which is based on the six-section aero-lithium battery pack as the object of detection. The effective iterative calculation of State of Charge (SOC) value is realized by simplifying the process of three-particle and double Sigma processing. The accuracy of the method is verified by comparing the simulation results with the actual measurement results. Experimental results show that the error of this method is less than 3.00%, which effectively improves the SOC estimation accuracy and is of great significance to energy management and safety assurance of power lithium-ion battery packs.

1. Introduction

During the whole life cycle of power lithium battery pack, the monitoring and regulation of SOC, the core parameter of battery management system, will affect the output effect and safety. Therefore, it is necessary to monitor the change of the parameters in real time and ensure the performance of lithium battery pack based on this. The development of lithium-ion battery packs is seriously restricted by the potential safety hazards in the use of BMS because the estimation technology of group SOC is not mature. For power lithium batteries, reliable BMS management relies on accurate SOC values. When this value is known, not only reliable energy management and safety control can be carried out, but also early damage of lithium battery pack can be avoided and its service life can be prolonged. Therefore, accurate estimation of SOC is very important to ensure the performance, energy and safety management of power lithium battery pack.

In view of the problems of energy management and safety control of power lithium-ion battery packs, scholars at home and abroad have carried out in-depth research on the basis of the open circuit voltage (OCV) and the ampere-time integration method. Feng et al. proposed the Kalman correction algorithm by making full use of the modified function of Extended Kalman Filter (EKF). The estimation error was less than 6.00% [1]. Shen et al. carried out the lithium ion electricity on the basis of the equivalent model analysis. The co estimation of the state of charge, the state of health and the functional state of a tank are studied [2]. Zheng et al have studied the error sources of on-line SOC estimation for Li ion batteries [3]. Nejad et al combined with equivalent circuit model are used to build real-time state estimation of lithium ion battery [4]. Ge et al built a real-time model-based SOC and State of Health (SOH) estimation for BMS [5]. Lim et al realized Fading Kalman Filter (KF) based on real-time SOC estimation in LIB-powered EVs [6]. Wei et al Enhanced online model identification...
and SOC estimation were realized for LIB by constructing an observer [7]. Liu et al proposed a new modeling and SOC estimation method for the LIB[8].

In view of the above analysis, this paper takes six aviation lithium batteries as the test object, establishes Thevenin equivalent circuit model, proposes an improved traceless transform SOC estimation, and designs a BMS system.

2. Theory and method research

2.1. Equivalent circuit modeling

By assuming that the six cells in the battery pack are identical, the whole battery pack is equivalent to a single cell with higher voltage and larger capacity. Based on the equivalent modeling analysis, the advantages and disadvantages of several equivalent models are analyzed respectively. Finally, because the Thevenin model is simple in structure, easy to identify parameters, considering the polarization phenomenon of the battery, this paper chooses to use that model to describe the battery response behavior to be more accurately, as shown in Figure 1.

![Thevenin equivalent model structure diagram](image)

Figure 1. Thevenin equivalent model structure diagram.

Figure 1 shows that \( U_{oc} \) is open circuit voltage, \( R_0 \) is ohmic internal resistance, and \( R_P \) and \( C_P \) are polarization resistors and polarization capacitors respectively. \( U_L \) is the closed-circuit voltage after the battery pack is connected with the load. According to the basic characteristics of the capacitor, the relationship between the current flowing through \( C_P \) and its two closed-circuit voltages is obtained as shown in formula 1.

\[
I_{cp}(t) = C_P \frac{dU_{oc}(t)}{dt}
\]  

(1)

Based on the analysis of equivalent circuit constitution, according to Kirchhoff voltage law, the voltage relation in Figure 1 is shown in Formula 2.

\[
R_0 \frac{dU_{oc}(t)}{dt} + R_P \frac{U_{oc}(t)}{R_P} + U_{cp}(t) = U_{oc} - U_L
\]  

(2)

Considering \( U_{cp}(t) \) as the state variable, the above two expressions are combined to describe the comprehensive working state. The calculation process is analyzed, and the state space formula of the equivalent model is obtained, as shown in Formula 3.

\[
R_0 \frac{dU_{oc}(t)}{dt} + \left[1 + \frac{R_0}{R_P}\right] U_{cp}(t) = U_{oc} - U_L
\]  

(3)

The five parameters of \( U_{oc} \), \( R_{th} \), \( R_P \), \( C_P \) and \( U_L \) in the equivalent circuit model of the battery pack need to be identified. The mixed pulse power performance of the three-component 50Ah lithium battery pack of AVIC is tested at 25C to get the parameters at each SOC point.

2.2. Reduced particle unscented Kalman SOC estimation

Aiming at the accurate estimation of the SOC value of lithium battery pack, this paper proposes a method of particle unscented transformation. By simplifying the three-particle and double Sigma processing process, the effective iterative calculation of the SOC value of lithium battery pack is realized. The idea of reduced particle unscented transformation is applied to the prediction and modification, and the establishment of the lithium battery SOC estimation model and the mathematical iterative operation of the SOC value are realized. The principle is shown in Figure 2.
In Figure 2, the unscented transform shows good performance in the SOC estimation process. The transformation process is based on direct curve fitting and unscented Kalman evaluation, and has stronger adaptability to the nonlinear features. The idea of using the simplified three-particles is reasonable and has the advantage of small amount of calculation.

In Figure 3, the S1 phase represents the calculation process of the state formula, and the S2 phase represents the calculation process of the observation formula. In order to make the estimation process have better stability and higher precision, the unscented transformation is introduced into the SOC estimation process. So that it does not require Jacobian matrix calculations for state formula s and observation formula s. Based on this process, the SOC statistical characteristics of the lithium battery pack are calculated. Its data set is obtained by formula 4.

\[
\begin{align*}
SOC^{(0)} &= SOC, t = 0 \\
SOC^{(i)} &= SOC + \left( (n + \lambda)P \right)_{i}, t = 1, \ldots, n \\
SOC^{(n)} &= SOC - \left( (n + \lambda)P \right)_{i}, t = n + 1, \ldots, 2n \\
\end{align*}
\]

(4)

In formula 4, n represents the state dimension of the data sets, i represents the ith column of the sample data sequence and its covariance matrix. the variance P is the product of the transpose of the arithmetic square root and the square root of the operator.

The detection data points of lithium battery pack are obtained by screening the original state distribution of the state values. Then, the target sampled data points are selected into the state formula and observation formula. Then the corresponding weights of these sampling points are calculated, and the weight coefficient of the sample data series is obtained by formula 5.

\[
\begin{align*}
\alpha_{0} &= \frac{\lambda}{n + k}, \lambda = \alpha^{2}(n + k) - n \\
\alpha_{1} &= \frac{\lambda}{n + k}, \lambda = (1 - \alpha^{2} + \beta) \\
\alpha_{2} &= \frac{1}{2(n + k)} \\
\end{align*}
\]

(5)

In the formula, the subscript m is the mean value, representing the mean value of the Sigma data point set about SOC. C is the covariance, representing the variance of the Sigma data point set about SOC value. the superscript I is the second sampling point, indicating the sequence number of the sampling data points. λ is the overall scaling scale coefficient, and the error of SOC estimation can be reduced by adjusting the value of the parameter. \(\lambda = \alpha^{2}(n + k) - n\) is a scalar parameter to characterize the scaling ratio, which is used to reduce the estimation error of SOC. the selection of \(\alpha\) determines the
state distribution of SOC value sequence, and then the value of parameter $\kappa$ is obtained on the premise that the matrix $(n + \lambda) P$ is a semi-positive definite matrix through the selection of non-negative weight coefficient $\beta$, the higher order term of state space formula is incorporated. Statistical error is used to ensure that the influence of higher-order terms is included in the unscented transformation.

For $k$ at different time points, the SOC estimation process includes SOC, a random state variable fused with gaussian white noise $w(k)$, and $U_L(k)$, an observation random variable integrated with gaussian white noise $v(k)$. $F(*)$ is a nonlinear state formula used to describe the SOC state of lithium battery pack. $G(*)$ is a nonlinear observation formula used to describe the characteristics of the output closed circuit voltage. The variance of the noise matrix $w(k)$ is described by $Q$, while the variance of the noise matrix $v(k)$ is described by $R$. Under the influence of random noise, for the lithium battery group SOC to accurately estimate the target, the estimation of $k$ at different time is realized through the following steps.

S1: A series of sample points are used to form the sequence of Sigma data points, and the corresponding weight coefficients are obtained by untracked transformation, as shown in formula 6.

$$
SOC^{(\beta)}(k-1) = \sum_{i=1}^{2n+1} \beta_i \cdot SOC^{(i)}(k-1)
$$  \hspace{1cm} (6)

S2: The first order prediction of Sigma data point sequence with length $2n+1$ is calculated, and the calculation process is described in formula 7.

$$
SOC^{(0)}(k|k-1) = \hat{f}[k, SOC^{(i)}(k-1)], i=1,2,\cdots,2n+1
$$  \hspace{1cm} (7)

S3: Calculate the one-step prediction of the state space variable and its variance matrix, perform the weighted summation of the sigma data point sequence, realize the prediction process by setting the three data points, and calculate the average value by combining the weighting coefficients. The calculation process of the SOC prediction value is used. Formula 8 is described.

$$
SOC(k|k-1) = \frac{1}{\sum_{i=1}^{2n+1} \beta_i} SOC^{(i)}(k|k-1)
$$  \hspace{1cm} (8)

The Predicted value of SOC state variance is obtained, and the calculation process is shown in formula 9.

$$
P(k|k-1) = \sum_{i=1}^{2n+1} \beta_i \left[ SOC(k|k-1) - SOC^{(i)}(k|k-1) \right] \left[ SOC(k|k-1) - SOC^{(i)}(k|k-1) \right]^T + Q
$$  \hspace{1cm} (9)

S4: The new Sigma data point sequence used in SOC estimation process is obtained by applying untracked transformation to the one-step predicted value again, and its calculation process is shown in formula 10.

$$
SOC^{(0)}(k|k) = \sum_{i=1}^{2n+1} \beta_i \cdot SOC^{(i)}(k|k-1)
$$  \hspace{1cm} (10)

S5: The Sigma data point sequence obtained in the previous step is substituted into the observation formula of the SOC estimation model, and the predicted observed variable matrix is obtained as shown in formula 11.

$$
U^{(0)}_L(k|k) = h[SOC^{(0)}(k|k-1)], i=1,2,\cdots,2n+1
$$  \hspace{1cm} (11)

S6: The predicted mean value of the output closed-circuit voltage and its autocorrelation matrix and cross-correlation matrix are calculated and used for the correction of the SOC estimation. The calculation process is as follows.

(1) The predicted mean value is as shown in formula 12.

$$
\bar{U}_L(k|k-1) = \sum_{i=1}^{2n+1} \beta_i \cdot U^{(i)}_L(k|k-1)
$$  \hspace{1cm} (12)

(2) The autocorrelation matrix is as shown in formula 13.

$$
R^{(0)}_{U_L(k|k)} = \sum_{i=1}^{2n+1} \beta_i \left[ U^{(i)}_L(k|k-1) - \bar{U}_L(k|k-1) \right] \left[ U^{(i)}_L(k|k-1) - \bar{U}_L(k|k-1) \right]^T + R
$$  \hspace{1cm} (13)
(3) The cross-correlation matrix is as shown in formula 14.

\[
P_{\text{SOC}(i,k|k-1)} = \sum_{n} \alpha^{n} [U_z^{(i)}(k|k-1) - \bar{U}_z(k|k-1)] [U_z^{(i)}(k|k-1) - \bar{U}_z(k|k-1)]^T
\]  

(14)

(4) The Kalman gain matrix of the SOC estimation of the lithium battery pack is obtained by the calculation process of formula 15.

\[
K(k) = P_{\text{SOC}(i,k|k-1)} P^{-1}_{\bar{U}_z(k|k-1)}
\]  

(15)

(5) The status update is calculated by formula 16.

\[
\text{SOC}(k) = \text{SOC}(k|k-1) + K(k) [U_z(k) - U_z(k|k-1)]
\]  

(16)

(6) The error covariance update is obtained by calculation of formula 17.

\[
P(k) = P(k|k-1) - K(k) P_{\text{SOC}(i,k|k-1)} K^T(k)
\]  

(17)

The sample sequence data set is used to approximate the posterior probability density of the SOC estimation process, so that the statistical feature has the advantage of high precision, which effectively reduces the nonlinear error in the SOC estimation process. On the basis of the streamlined three-particle transform, the data weighted mean calculation is performed using the two weightings processing of Sigma data points. The SOC estimation model of the lithium battery pack is constructed.

3. Hardware design and implementation

Real-time monitoring of the battery pack and accurate estimation of SOC. Design a micro-distributed intelligent battery management system. Ensure that the SOC is maintained within a reasonable range and predict how much energy is left in the battery pack or the state of charge of the battery pack. The BMS system was designed for the six-cell battery pack condition monitoring target. The STM32+ integrated chip sampling modular design, the total size of 50*80mm is smaller than the mobile phone screen. The PCB circuit of BMS is shown in Figure 4.

![Figure 4. Battery management system PCB placed side-by-side to save space.](image)

The BMS device was designed and implemented and verified by a lithium battery pack. A picture of the relevant BMS device is shown in Figure 5.

![Figure 5. Battery management system physical map.](image)

The system is aimed at detecting and managing the status information of lithium-ion battery packs. It has single-cell voltage and high-precision real-time detection of SOC. Its voltage accuracy is 1mV, featuring low power consumption, high integration and small size.

4. Experiment and analysis

4.1. Relationship between OCV and SOC

Taking the aviation lithium battery pack as the detection object, based on the battery management system hardware, the 0.3C, 0.5C, 1C constant current discharge experiments were performed on the lithium battery pack and fitted, and finally the curve of VOC and SOC are obtained, as shown in Figure 6. Shown below.
It can be seen from Figure 6 that when the SOC is between 0 and 0.1 and between 0.9 and 1, the VOC changes very sharply, and the relationship between the two is nonlinear. The SOC is between 10% and 90% where VOC varies smoothly with the SOC. The relationship is at that points is linear.

4.2. HPPC experiment
Aiming at the acquisition target of the lithium battery pack Thevenin model parameters, a variety of charge-discharge pulse combination experiments were carried out, and then the experimental model analysis and calculation process principle analysis were carried out to obtain the model coefficients in the equivalent model and their variation with the working state. The HPPC experimental process is shown in Figure 7.

The closed-circuit voltage response of the lithium battery pack was obtained by HPPC experiment under different SOC conditions for its parameter identification. The coefficients of the functional formula are obtained by the closed-circuit voltage response of the battery pack in combination with HPPC, and the parameter function relationship of Thevenin model is obtained by processing these coefficients.

4.3. SOC estimation experiment analysis
In order to verify the effect of the designed BMS, the aviation lithium battery pack was selected as the experimental sample. Through the relevant experimental research, the estimated performance was verified by the pulse characteristic experiment and the open circuit voltage curve. The estimation results are shown in the figure below by estimating the state during the discharge maintenance process.

It can be seen from Figure 8 that the designed SOC estimation method has a good tracking effect for the aviation lithium battery pack. It has a good correction effect on the initial error. After repeated experiments, the method achieves the goal of accurate estimation of SOC for aviation lithium-ion battery packs.

5. Conclusions
Based on the unscented transformation, this paper proposes a simplified particle unscented Kalman filter algorithm and constructs a model to realize the recursive operation of the aviation lithium battery SOC. The linearization process is streamlined to reduce the offset of the SOC estimation results. In the estimation model, the Thevenin state space formula is integrated to improve the computational efficiency. The nonlinear transformation is optimized by the reduced transformation, and the closed-circuit voltage feedback correction is combined to obtain the current group SOC value. The experimental results show that the estimation error of the method is less than 3.00% during charge and discharge. And the designed BMS system can perform real-time detection with a voltage accuracy of 1mV, featuring low power consumption, high integration, and a small size.
Figure 8. SOC estimation result.

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