Lithium battery state of charge and state of health prediction based on fuzzy Kalman filtering

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Abstract: This paper presents a more accurate battery state of charge (SOC) and state of health (SOH) estimation method. A lithium battery is represented by a nonlinear two-order resistance-capacitance equivalent circuit model. The model parameters are estimated by searching least square error optimization algorithm. Precisely defined by this method, the model parameters allow to accurately determine the capacity of the battery, which in turn allows to specify the SOC prediction value used as a basis for the SOH value. Application of the extended Kalman filter (EKF) removes the need of prior known initial SOC, and applying the fuzzy logic helps to eliminate the measurement and process noise. Simulation results obtained during the urban dynamometer driving schedule (UDDS) test show that the maximum error in estimation of the battery SOC is 0.66%. Battery capacity is estimate by offline updated Kalman filter, and then SOH will be predicted. The maximum error in estimation of the battery capacity is 1.55%.

Key words: lithium battery; state of charge (SOC); state of health (SOH); adaptive extended Kalman filter (AEKF)

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0 Introduction

Rapid transport and economy development inevitably increase global challenges, such as global warming and air pollution. Therefore, in recent years, more and more attention is paid to electric vehicles because of their efficiency and environmental friendliness. The battery is one of the most important and expensive components of an electric vehicle. The development of new technologies related to batteries has an impact over the electric transport industry. Battery management systems (BMS) controls the operation of the battery. In order to ensure a safe operation of the electric vehicle, prevent deep discharge or overcharging of the battery, accurately estimate residual mileage, extend the lifetime, prevent progressively permanent damage to the battery and maximize battery performance, the BMS must have an accurate value of state of charge (SOC). In addition, to improve the reliability of operation and to warn the driver about the future replacement of the battery, the BMS needs the value of state of health (SOH).

Processes and chemical reactions proceeding inside lithium battery are complex and nonlinear. Work processes are influenced by residual capacity of battery, voltage, temperature, current, aging, internal resistance, self-discharge, charge-discharge cycle number and other factors. Therefore, SOC estimation problem are complex and important, but existing SOC prediction methods have relatively large error.

Battery SOC can be calculated by the Coulomb counting method or the open circuit voltage method[1-2]. These two methods are simple and easy to apply at practical terms. However, these methods have disadvantages: both of them are open-loop and sensitive to the sensor precision. Moreover, open circuit voltage-SOC curve is flat on wide SOC range that makes it impossible to estimate SOC accurately. Therefore, estimation errors in all of these methods are very high. Some generic methods, such as a neural networks, fuzzy logic and support vector machine, have provided "black box" SOC

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estimation[3-5]. The main weak points of these methods are their sensitivity to amount and quality of training data. Advanced methods, such as the Kalman filter and sliding observers, are based on linear dynamic systems discretized in the time and estimator[6-7], and only estimate the state from the previous time step and the current measurements. However, these methods highly depend on the model accuracy, and are the most complicated in the aspect of computing. Although the extended Kalman filter (EKF) can provide good estimation results, this method is not suitable for non-Gaussian noise and highly nonlinear systems because of large cumulative estimation error. To improve the accuracy of SOC estimation, the adaptive extended Kalman filter (AEKF) algorithm has been applied. The value of the measurement noise covariance is adaptively adjusted in the estimation process, thus improving the estimation accuracy.

Some methods have low estimation accuracy, also most of the methods above deal only with SOC and do not take into account battery degradation and its SOH. Nevertheless, accuracy of SOC estimation is heavily influenced by the battery aging condition. Inaccurate calculation of SOC will reduce vehicle performance in case of undercharging or even may cause damage to the battery system due to overcharging. Therefore, the needs of accurate battery states prediction are urgent.

Therefore, at first, the proposed method improves SOC prediction accuracy by improving accuracy of estimation model parameters. Second-order equivalent circuit model best of all reflects a real battery state and searching model parameters optimization algorithm has relatively good performance. Secondly, through applying of adaptive EKF algorithm, self-adjusted measurement noise removes the demand of prior known initial covariances, thereby improving SOC estimation accuracy. Finally, the accurate SOC value increases SOH prediction algorithm efficiency.

In this paper, the lithium battery equivalent circuit model is represented. Model parameters are estimated in discharging test by least square error optimization algorithm. Based on model parameters and state space equations, AEKF estimates SOC. Then, the battery SOH is predicted by estimating battery capacity Kalman filter. Efficiency of prediction is validated in the urban dynamometer driving schedule (UDDS) test.

1 Battery modelling

1.1 Equivalent circuit model

There are many types of equivalent circuit models used to describe lithiumion battery work, such as Rint model, Thevinin model, the partnership for a new generation of vehicles (PNGV) model, etc. However, because of processes nonlinearity, some of them cannot reflect a real cell process carefully, which leads to comparatively large modeling error[8].

As shown in Fig. 1, every discharge pulse actually leads to nonlinear voltage response, containing the instantaneous part caused by battery resistance and delayed part caused by battery capacity.

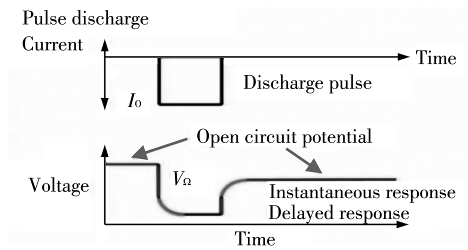


Fig. 1 Real process nonlinearity

The best model reflecting the real state of battery for today is the second-order equivalent model[9], as shown in Fig. 2. It consists of the open circuit voltage (OCV) E_0, battery ohmic resistance R_0, and two sets of parallel resistor-capacitor combination R_1, C_1 and R_2, C_2 representing the mass transport effect and the double layer effect, respectively.

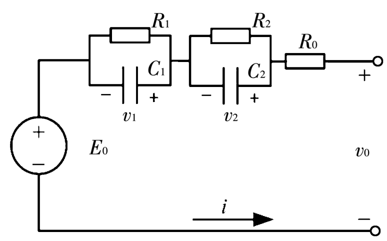


Fig. 2 Second-order equivalent circuit model

According to the model, battery electrical behavior can be expressed by

$$v_0 = E_0 + v_1 + v_2 + iR_0, \tag{1}$$

$$i = \frac{v_1}{R_1} + C_1 \frac{\mathrm{d}v_1}{\mathrm{d}t} = \frac{v_2}{R_2} + C_2 \frac{\mathrm{d}v_2}{\mathrm{d}t}. \tag{2}$$

Coulomb-counting SOC definition is[10]

$$s = s_0 - \frac{\eta}{Q_r}\int_0^t i(t)\mathrm{d}t, \tag{3}$$

where s_0 is the initial SOC, η is the Coulomb efficiency coefficient and Q_r is the battery rated capacity. Combining Eqs. (1), (2) with (3), we obtain the battery state space equation in discrete form

$$\begin{bmatrix} s_{k+1} \\ v_{1,k+1} \\ v_{2,k+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \mathrm{e}^{-T/\tau_1} & 0 \\ 0 & 0 & \mathrm{e}^{-T/\tau_2} \end{bmatrix} \begin{bmatrix} s_k \\ v_{1,k} \\ v_{2,k} \end{bmatrix} + i_{t,k} \begin{bmatrix} -\eta T/Q_r \\ R_1(1-\mathrm{e}^{-T/\tau_1}) \\ R_2(1-\mathrm{e}^{T/\tau_2}) \end{bmatrix} + \begin{bmatrix} w_{1,k} \\ w_{2,k} \\ w_{3,k} \end{bmatrix}, \tag{4}$$

$$v_{0,k} = E_{0,k} + v_{1,k} + v_{2,k} + i_{tmk} R_0 + v_k, \tag{5}$$

where $\tau_1 = R_1 C_1$, $\tau_2 = R_2 C_2$, and $\boldsymbol{x}_k = [s_k, v_{1,k}, v_{2,k}]^{\mathrm{T}}$ are state variables; $i_{t,k}$ is the control variable; $v_{0,k}$ is the measurement variable; $\boldsymbol{w}_k = [w_{1,k}, w_{2,k}, w_{3,k}]^{\mathrm{T}}$ is the process noise with covariance $\boldsymbol{Q}$; and v_k is the measurement noise with covariance $\boldsymbol{R}$.

1.2 Model parameters estimation and validation

Model parameters cannot be taken as constants because of their changes under different battery temperatures and ages. To complete state space equation and apply an EKF algorithm, the model parameters must be estimated. In order to provide better online prediction of SOC, truly estimate the battery capacity Q_r, and reduce future errors in the following steps, it is essential to estimate the model parameters as accurately as possible. Some researchers use genetic algorithm or nonlinear curve fitting technics for searching parameters at definite space, but these methods require good quality of initial parameter values and searching space. This paper presents a parameter estimation technology based on Matlab parameter estimation tool algorithm. The parameters estimated by nonlinear least squares optimization method namely Levenberg-Marquardt algorithm. The algorithm minimizes the sum square error on the test data, as shown in Fig. 3.

Levenberg-Marquardt (LM) method is a good optimization algorithm, which can adaptively adjust itself to the gradient-descent or Gauss-Newton method depending on the distance from optimal values. In addition, LM algorithm has faster convergence and better efficiency compared to both methods that are mentioned above.

Nonlinear least squares regression object function is expressed as

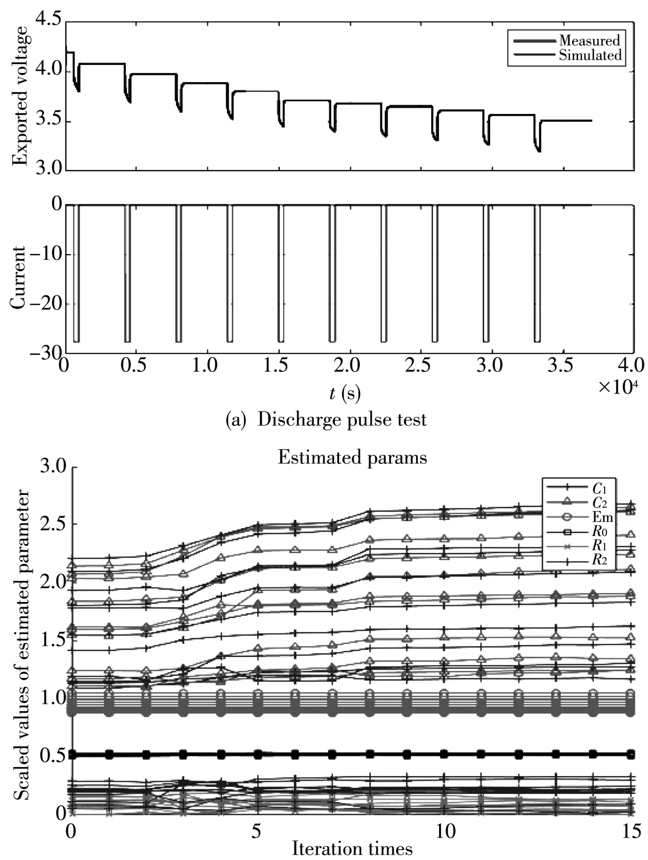
$$\min_{\boldsymbol{\theta}} \sum_{i=1}^{N} (y_{\mathrm{m}}(t_1) - y(t_i, \hat{\boldsymbol{\theta}}))^2, \tag{6}$$

where $y_{\mathrm{m}}(t_i)$ is the measured voltage, and $y_{\mathrm{m}}(t_i, \hat{\boldsymbol{\theta}})$ is the model predicted voltage with parameter vector $\boldsymbol{\theta}$.

The LM algorithm is used to solve the optimization problem of Eq. (6) by adding the parameter correction vector, and then we get

$$\Delta\boldsymbol{\theta} = (\lambda \boldsymbol{I} + \boldsymbol{J}^{\mathrm{T}}\boldsymbol{J})^{-1}\boldsymbol{J}^{\mathrm{T}}(\boldsymbol{Y}_{\mathrm{m}} - \boldsymbol{Y}), \tag{7}$$

where $\boldsymbol{J}$ is the Jacobian matrix, $\boldsymbol{Y}$ is the vector of the predicted voltages, $\boldsymbol{Y}_{\mathrm{m}}$ is the vector of the measured voltages, and λ is the damping factor.



(a) Discharge pulse test

(b) Parameters estimation process

Fig. 3 Parameter estimation by Levenberg-Marquardt optimization algorithm.

Parameters estimation algorithm efficiency is validated by discharging test on the simulation data set, and sum square error is about 0.000 1.

2 SOC estimation with adaptive extended Kalman filter

Kalman filter is a reducing mean square error mathematic technique commonly used for estimating the system states. One significant disadvantage of Kalman filter is its assumption that covariance of measurement and process noises are known. This peculiarly brings a large error in some cases, such as wrong or unknown initial noise. Therefore, in these conditions, EKF, which can adaptively adjust noise covariance, can reach better estimation performance.

Generally, EKF uses further state-space framework as

$$\boldsymbol{X}_{k+1}=\boldsymbol{A}\boldsymbol{x}_k+\boldsymbol{B}\boldsymbol{u}_k+\boldsymbol{w}_k, \tag{8}$$

$$\boldsymbol{Y}_{k+1}=\boldsymbol{C}\boldsymbol{x}_{k+1}+\boldsymbol{D}\boldsymbol{u}_k+\boldsymbol{v}_k, \tag{9}$$

where $\boldsymbol{x}_k$ is a system state vector, $\boldsymbol{w}_k$ is a system process noise, $\boldsymbol{v}_k$ is a measurement noise. $\boldsymbol{w}_k$ and $\boldsymbol{v}_k$ both are the zero mean Gaussian noise with time-invariant covariance $\boldsymbol{Q}_k$ and R_k, respectively. $\boldsymbol{Y}_k$ is system output estimates. $\boldsymbol{A}$, $\boldsymbol{B}$, $\boldsymbol{C}$ and $\boldsymbol{D}$ are matrices, describing dynamics of the system.

The process noise for the SOC, v_1 and v_2 will be estimated based on dynamic characteristics of the battery of Eq. (3). The duration of one charge-discharge cycle is about 5 000 s. The maximum change is 100% for SOC, and around 2 V for v_1 and v_2. The maximum change per step for SOC is

$$\max(|\mathrm{d}\delta_{\mathrm{SOC}}|)\approx\frac{100\%}{5\ 000}T. \tag{10}$$

And for v_1 and v_2, there is

$$\max(|\mathrm{d}v_1|)=\max(|\mathrm{d}v_2|)\approx\frac{2}{5\ 000}T, \tag{11}$$

where T=1 s is filter sampling time.

Therefore, the process noise $\boldsymbol{w}_k$ is expressed as

$$\boldsymbol{w}_k=\begin{bmatrix}\max(|\mathrm{d}\delta_{\mathrm{SOC}}|)^2 & 0 & 0\\ 0 & \max(|\mathrm{d}v_1|)^2 & 0\\ 0 & 0 & \max(|\mathrm{d}v_2|)^2\end{bmatrix}\approx\begin{bmatrix}4\times10^{-8} & 0 & 0\\ 0 & 1.6\times10^{-7} & 0\\ 0 & 0 & 1.7\times10^{-7}\end{bmatrix}. \tag{12}$$

Process noise initial covariance shows how accurate the initial guess is. Assuming that the maximum initial guess error is 40% for SOC and 1 V for v_1 and v_2, we obtain the following initial covariance matrix, which consists of squares of initial guess errors as

$$\boldsymbol{Q}_0=\begin{bmatrix}0.16 & 0 & 0\\ 0 & 1 & 0\\ 0 & 0 & 1\end{bmatrix}. \tag{13}$$

The main idea of AEKF is to provide self-adaptation to the system measurement noise covariance $\boldsymbol{R}$. The purpose of adaptive approach is to make the theoretical noise covariance stay in step with the actual noise covariance using fuzzy logic. The adaptive approach several steps are as follows:

Step 1) Theoretical measurement noise

$$\boldsymbol{N}_{\mathrm{t}}=\boldsymbol{C}_k\boldsymbol{P}_k^{-1}\boldsymbol{C}_k^{\mathrm{T}}+\boldsymbol{R}_k. \tag{14}$$

Step 2) Actual measurement noise

$$\boldsymbol{N}_{\mathrm{a}}=\frac{1}{n}\sum_{i=i_0}^{k}\boldsymbol{r}_i\boldsymbol{r}_i^{\mathrm{T}}, \tag{15}$$

where $\boldsymbol{r}_k=\boldsymbol{Y}_{k-1}-\boldsymbol{C}_k x_{k-1}$ is EKF residual sequence.

Step 3) Difference between actual noise and theoretical noise

$$\Delta\boldsymbol{N}=\boldsymbol{N}_{\mathrm{i}}-\boldsymbol{N}_{\mathrm{a}}. \tag{16}$$

On this step, fuzzy logic is applied. If the difference between the actual and theoretical measurement noise $\Delta\boldsymbol{N}$ is greater than zero, noise covariance $\boldsymbol{R}_k$ will be reduced. Otherwise, when $\Delta\boldsymbol{N}$ is smaller than zero, $\boldsymbol{R}_k$ will be increased. Noise covariance value $\boldsymbol{R}_k$ is controlled and automatically corrected by the adjustment factor α

$$\boldsymbol{R}_k=\alpha\boldsymbol{R}_{k-1}. \tag{17}$$

In order to provide auto-updating measurement, noise covariance fuzzy logic controller with ΔN input and α output were shown in Table 1.

Table 1 Input and output fuzzy subsets

Variable and range	Fuzzy subset	Value
ΔN [−1.5 1.5]	Highly negative	[−1.5 −1 −0.5]
	Negative	[−1 −0.5 0]
	Zero	[−0.5 0 0.5]
	Positive	[0 0.5 1]
	Highly positive	[0.5 1 1.5]
α [0.5 1.5]	Greatly decrease	[0.25 0.5 0.75]
	Slightly decrease	[0.5 0.75 1]
	Unchanged	[0.75 1 1.25]
	Slightly increase	[1 1.25 1.5]
	Greatly increase	[1.25 1.5 1.75]

According to Eqs. (14)−(17), fuzzy logic rules are formulated as follows:

1) If $\Delta\boldsymbol{N}$ is highly negative, than greatly increase α.

2) If $\Delta\boldsymbol{N}$ is negative, α slightly increases.

3) If $\Delta\boldsymbol{N}$ is zero, α is unchanged.

4) If $\Delta\boldsymbol{N}$ is positive, α slightly decreases.

5) If $\Delta\boldsymbol{N}$ is highly positive, α greatly decreases.

Adaptive fuzzy approach helps more accurate correct system measurement noise and increase EKF performance.

3 SOH prediction

During operation, the battery is aging, and its properties begin to deteriorate. The maximum capacity decreases, and the internal resistance increases. Correction of SOH prediction helps to assure safety operation of the electric vehicle and provide knowledge about the battery degradation degree. SOH is a parameter, which reflects the general conditions of the battery and its ability to deliver the specified performance compared with the fresh battery, and it is defined as

$$\delta_{\mathrm{SOH}} = \frac{C_{\mathrm{now}}}{C_{\mathrm{new}}} \times 100\%. \tag{18}$$

Good prediction of SOH is very important. In case of electric vehicles, the ability to achieve the announced range dramatically fades with battery aging. In this paper, SOH ranges from 0 to 100%. Among them, 0% SOH stands for end of life; when the battery capacity reaches 75% of fresh battery capacity, it has to be replaced; and 100% SOH stands for brand new fresh battery conditions, namely

$$C_{\mathrm{EOL}} = 0.75 C_{\mathrm{new}}. \tag{19}$$

Because parameters estimation error is very small in Fig. 3, the measurement capacity by integrating the current over a charge or discharge cycle (Coulomb counting) method is assumed to be reliable. Since the degradation rate of battery capacity C_i is not known in advance, it has been set to a random walk in state transition as

$$C_{i+1} = C_i + w_c, \tag{20}$$

where i is the number of charge-discharge cycles, w_c is the process noise. The measurement equation is expressed as

$$\hat{C}_i = C_i + v_c, \tag{21}$$

where $\hat{C}_i$ is the measured capacity, v_c is the measurement noise. The battery automatically charges until it reaches δ_{SOC_i}, and then turns to discharge until it reaches $\delta_{\mathrm{SOC}_{i-1}}$. Capacity measurement equation can be rewritten as

$$C_i = \frac{\int_{t_{i-1}}^{t_i} I \mathrm{d}t}{\delta_{\mathrm{SOC}_i} - \delta_{\mathrm{SOC}_{i-1}}} + v_c. \tag{22}$$

Then, offline event-based Kalman filter is applied.

4 Simulation results

In order to prove the effectiveness of the method above, a simulation was performed. Simulation object is the lithium battery with a rated voltage of 3.7 V and a rated capacity of 4.4 Ah. Battery height is 146 mm, weight is 85 mm and thickness is 3 mm. Firstly, the battery equivalent circuit model parameters were estimated based on the data obtained from the discharge test. Discharge pulse test consists of ten short discharge impulses, on condition that the time between pulses is at least 4 times longer than one pulse duration. This testing method allows getting the voltage nonlinearities caused by mass transport and double layer effects (Fig. 1) more accurately. The model parameters were optimized according to the reference terminal voltage signal until the sum square error reaches 0.000 1 (Fig. 3).

In order to take into account the temperature influence, model parameters were estimated three times at different temperatures (5, 25, 40 ℃). The resulting parameters were entered in look up tables for each element of the equivalent circuit model.

Then, the battery SOC was estimated by AEKF, using the measured current, voltage, temperature and estimated model parameters. During the UDDS test, the battery alternates between charging and discharging cycles, as shown in Fig. 4.

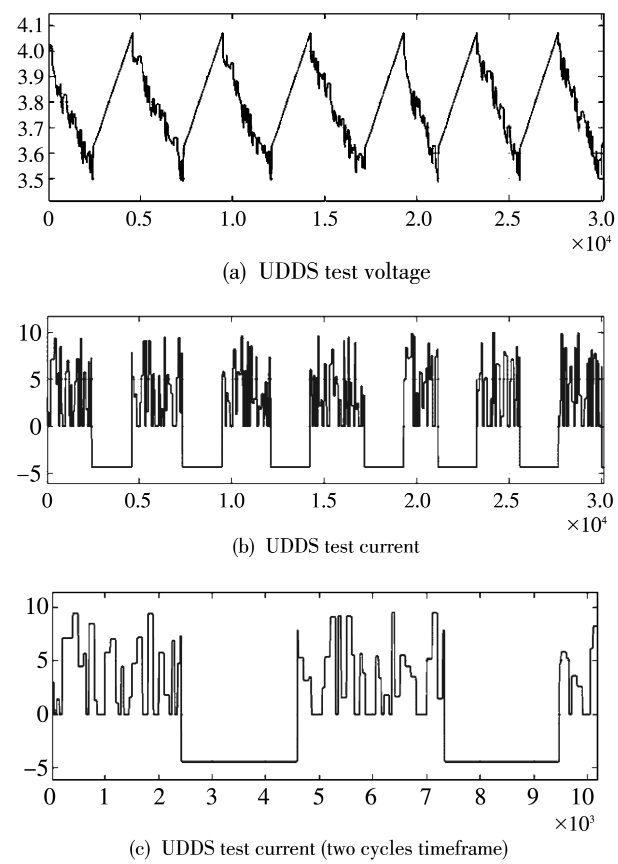
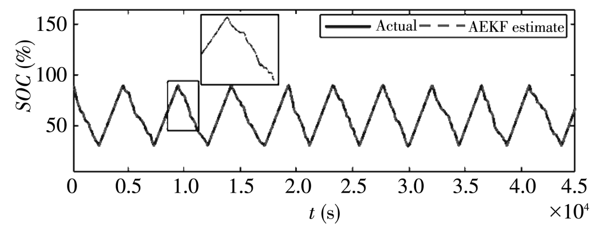
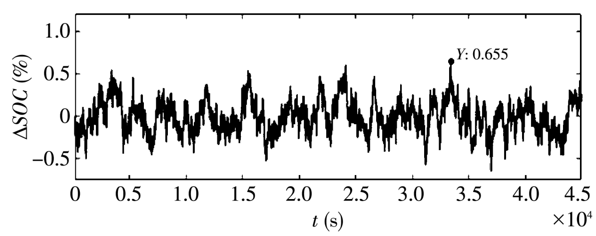


Fig. 4 UDDS test procedure

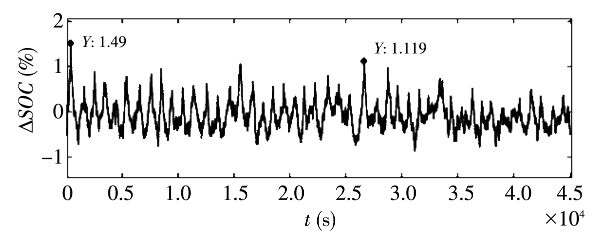
Battery discharged by random amplitude current pulses (from 1 to 10A), which imitates real city driving condition until it reaches 30% SOC, then turns to charging. Battery charges until it reaches 90% SOC, then again turns to discharge. During the test, AEKF estimates battery SOC based on measured voltage, circuit and model parameters according to procedure mentioned in Section 2. The experiment was conducted 15 times under the different conditions. Different randomly generated in UDDS test procedure current pulses statistically validate archived results. Simulation results show that AEKF reaches the best quality, as shown in Fig. 5.



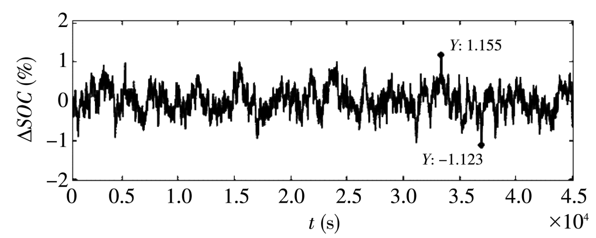
(a) SOC estimation by AEKF during UDDS test



(b) SOC estimation error (AEKF estimation)



(c) SOC estimation error (Coulomb counting estimation)



(d) SOC estimation error (EKF estimation)

Fig. 5 SOC prediction results

In average, the maximum error SOC value estimated by AEKF is 0.655% compared with the maximum error (1.49%) in the Coulomb counting estimation and the maximum error (1.155%) in the EKF estimation, respectively, as listed in Table 2.

Table 2 Compression of estimation methods

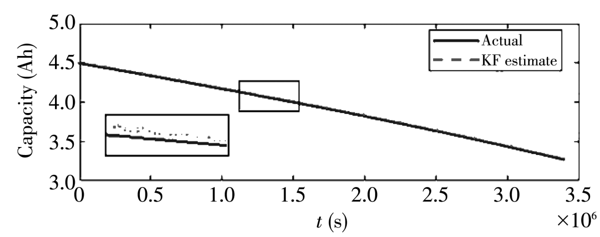
Estimation method	Coulomb counting	EKF	AEKF
Maximum error (%)	1.49	1.155	0.655

After successfully obtaining model parameters and SOC, the battery continues to operate according to the UDDS test until its capacity reaches 75% of the new battery capacity (end of life). At the time battery SOH considers to be 0. In this simulation, the battery's end of life is achieved after 813 charge-discharge cycles.

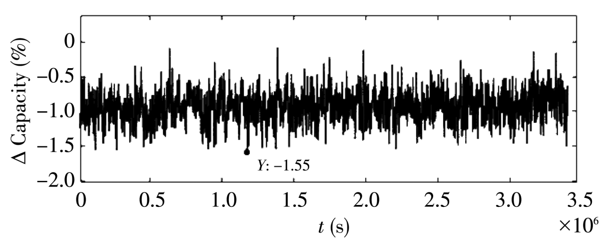
Battery capacity is rated by offline Kalman filter of Eqs. (20)−(21) based on the model parameters at the end of every cycle. Capacity prediction maximum error is 1.55%, as shown in Fig. 6. Then, according to the relationship between capacity and SOH is predicted, as listed in Table 3.

Table 3 Relationship between battery capacity and SOH

C_{now}	4.4	4.33	4.25	4.18	4.11	4.03	3.96	3.89
SOH	100	93	87	80	73	67	60	53
C_{now}	3.81	3.74	3.67	3.59	3.52	3.45	3.37	3.3
SOH	47	40	33	27	20	13	7	0



(a) Capacity estimation results



(b) Capacity estimation error

Fig. 6 Capacity estimation results

5 Conclusion

In this paper, an SOC and SOH prediction algorithm based on fuzzy Kalman filtering has been developed. The nonlinear model that takes into account the temperature of the battery and consists of two resistance-capacity circuit and open circuit voltage has been built. Model parameters have been estimated by optimization algorithm according to the test data. Battery SOC has been estimated by AEKF and validated under the close to real driving test cycle. Based on KF estimated battery capacity, SOH value has been predicted. Simulation results show that the proposed algorithm is reliable because of its high accuracy in predicting the parameters of both SOC and SOH. Moreover, the supposed algorithm does not need the exact initial condition.

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基于模糊卡尔曼滤波器的锂电池荷电状态与健康状态预测

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摘　要: 针对当前锂电池荷电状态(State of charge, SOC)与健康状态(State of health, SOH)预测精度较低的问题, 提出了一种基于模糊卡尔曼滤波器的预测方法。采用非线性二阶电阻电容模型表示锂电池, 并通过最小二乘误差优化算法对模型参数进行估计, 从而更准确地确定蓄电池容量作为 SOH 值的基础。扩展卡尔曼滤波器(Extended Kalman filter, EKF)可在初始 SOC 值未知的情况下对其进行准确预测, 而模糊逻辑有助于消除测量和过程噪声。仿真结果表明, 在城市测功机驱动计划期间(Urban dynamometer drving schedule, UDDS)测试中最大的 SOC 估算误差是 0.66%; 通过离线更新卡尔曼滤波器, 可对电池容量进行估计, 结果表明, 最大估计误差为 1.55%, 从而有效提高了 SOC 值的预测精度。

关键词: 锂电池; 荷电状态; 健康状态; 自适应扩展卡尔曼滤波器

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