Joint estimation of SOC and SOH for lithium-ion batteries based on EKF multiple time scales

Joint
estimation of
SOC and SOH

107

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Abstract

Purpose – The operation state of lithium-ion battery for vehicle is unknown and the remaining life is uncertain. In order to improve the performance of battery state prediction, in this paper, a joint estimation method of state of charge (SOC) and state of health (SOH) for lithium-ion batteries based on multi-scale theory is designed.

Design/methodology/approach – In this paper, a joint estimation method of SOC and SOH for lithium-ion batteries based on multi-scale theory is designed. The venin equivalent circuit model and fast static calibration method are used to fit the relationship between open-circuit voltage and SOC, and the resistance and capacitance parameters in the model are identified based on exponential fitting method. A battery capacity model for SOH estimation is established. A multi-time scale EKF filtering algorithm is used to estimate the SOC and SOH of lithium-ion batteries.

Findings – The SOC and SOH changes in dynamic operation of lithium-ion batteries are accurately predicted so that batteries can be recycled more effectively in the whole vehicle process.

Originality/value – A joint estimation method of SOC and SOH for lithium-ion batteries based on multi-scale theory is accurately predicted and can be recycled more effectively in the whole vehicle process.

Keywords Battery model, Multi-time scale extended Kalman filter, SOC estimation, Battery health status

Paper type Research paper

1. Introduction

The on-board battery is the main energy supply unit to drive the electric vehicle. The battery can provide the energy required for vehicle driving power and can also provide energy support for the electronic system of the whole vehicle. At the same time, the performance indexes related to the energy, power and multiplying power characteristics of the battery also significantly affect the performance of the vehicle. Therefore, the battery management system (BMS) and its key technology of real-time control module become the research focus of

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vehicle battery performance and battery monitoring system optimization (Yang *et al.*, 2019; Al-Zareer *et al.*, 2018; Zheng, 2017; Zhou, 2016; Ye *et al.*, 2020). In order to ensure the endurance of electric vehicle and protect the running state of battery pack at the same time, the collaborative estimation of state of charge (SOC), state of health (SOH), remaining useful life (RUL) and other issues of on-board battery is gradually becoming the focus of domestic and foreign scholars (Ma *et al.*, 2019; He *et al.*, 2015; Pattipati *et al.*, 2011).

The accurate estimation of SOC of lithium battery is studied in Zhang *et al.* (2018), Awadallah and Venkatesh (2016), Alfi *et al.* (2014), Charkhgard and Farrokhi (2010), Chen *et al.* (2013), He *et al.* (2011). Zhang *et al.* (2018), Awadallah and Venkatesh (2016), Alfi *et al.* (2014) used the neural network, learning algorithm and other different methods to accurately estimate the SOC of lithium battery. And the advantages and disadvantages of different methods are discussed. Extended Kalman filtering was applied to estimate the SOC of lithium-ion battery in Charkhgard and Farrokhi (2010), Chen *et al.* (2013), He *et al.* (2011). Chaoui *et al.* (2015), Gholizadeh and Salmasi (2014) jointly considers the SOC and SOH of lithium batteries, and Chaoui *et al.* (2015) proposes an adaptive strategy to estimating online parameters of the battery model using a Lyapunov-based adaptation law. Gholizadeh and Salmasi (2014) also consider inclusive models, using analytical methods to estimate additional non-linear or uncertainty terms in the model. This approach provides a very accurate model of the battery used in a battery management system. In addition, an online parameter estimation method is proposed to estimate the operating condition of the battery. Kim and Cho (2011), Kim *et al.* (2012) studies on the synergistic control of both SOC and SOH have used Kalman filtering combined with neural networks for the identification of cell models.

The coordinated control of SOC and SOH of battery is one of the important indicators to realize the balance of BMS. Although many scholars have done research in battery SOC control, but the synergistic control of SOC and SOH is still ineffective. Poor control can even reduce the driving performance of the vehicle, leading to a reduction in the life of the complete vehicle battery and the unknown safety of its use (Tong *et al.*, 2015; Yan *et al.*, 2019; Cannarella and Arnold, 2014). Predicting battery aging decay is one of the main difficulties in battery management, and studies have shown that the decay of SOH is closely related to factors such as temperature, cycle times, charge/discharge depth and current. Therefore, accurate real-time online monitoring by SOH can provide effective support for the balanced regulation of vehicle batteries (Chen *et al.*, 2020; Zhang *et al.*, 2020; Murariu and Morari, 2019). From the actual vehicle operating environment, it can be concluded that SOC is one of the influencing parameters for studying and evaluating SOH attenuation.

2. Method based on analysis model

2.1 Establishment of aging model of lithium-ion battery

Li-ion battery packs will suffer from self-discharge and leakage due to prolonged outage and the actual SOC value will also be inaccurate. The relationship between capacity and charge discharge times can be obtained by aging model of lithium-ion battery (Wei *et al.*, 2019; Ishizaki *et al.*, 2015). In this paper, the typical exponential model is selected to build the corresponding aging model, and the capacity decay data in the process of battery charging and discharging are used to fit continuously. The corresponding exponential aging model is described as shown in Eqn. (1).

$$C_{ek} = C_{ek1} + C_{ek2} = a_1 \cdot e^{a_2 \cdot k} + a_3 \cdot e^{a_4 \cdot k} \quad (1)$$

where C_{ek} is the rated capacity of index cell degradation model after the k -th charge and 1 discharge. a_1 , a_2 , a_3 , a_4 is the unknown parameter of the model, which needs to be identified.

The equivalent circuit model consists of three parts: the equivalent analysis of the model, the correlation between OCV and SOC and the identification of resistance and capacitance parameters (Lin *et al.*, 2017). Based on the analysis of short-term capacity aging characteristics, a capacity model and an aging model are established to fit the change trend of vehicle battery in the aging process. At the same time, comparing the exponential model with the polynomial model, it is not difficult to find that the exponential model is more suitable for building the corresponding aging model.

2.2 Equivalent model of lithium-ion battery

To establish a battery equivalence model, the main parameters of the model are needed to be obtained, i.e. internal variables, capacity, internal resistance and other characterization parameters of the battery. Predicting SOH by the developed model can get the value of SOH more directly. However, the disadvantage of pre-processing the measurement data makes it difficult to balance efficiency and real-time performance (Song *et al.*, 2020; Stroe and Schaltz, 2020). At the same time, due to the accuracy of estimation, the estimation methods based on the equivalent model method and electrochemical method cannot be directly used in other batteries. In the case of stable working environment, the method based on experience and characteristics will have a good performance. Due to the special dependence of the empirical model and the characteristic model, it cannot perform well under complex conditions. With the convenience of data acquisition and storage, data-based methods have become common, which can also predict the SOH of the battery and eliminate the fault. The method also suffers from certain shortcomings due to the time-consuming nature of data collection and the variability of working conditions (Ye and Li; Liu *et al.*, 2018; Roscher and Sauer, 2011). The different methods mentioned above have their own advantages and disadvantages. In this paper, based on the research of domestic and foreign scientific and technological workers, the applicability, high precision and real-time characteristics of the direct method will be combined to carry out online capacity prediction, so as to directly calculate the corresponding SOH value.

By using Kirchhoff's current and voltage theorem, the parameters of Thevenin equivalent circuit model (as shown in Figure 1) can be obtained from Eqns. (2) and (3).

$$V_s = -\frac{1}{R_s C_s} V_s + \frac{1}{C_s} i \quad (2)$$

$$V = V_{oc}(\text{SOC}) + V_s + iR_i \quad (3)$$

$$\text{SOC} = \text{SOC}_0 + \int_0^t \frac{\eta i}{C_t} d\tau \quad (4)$$

where SOC_0 is the initial value of the battery static state, η is the process operation efficiency of the whole vehicle and C_t is the vehicle battery capacity with time as the independent variable.

Take $x = [S \ V_s]^T$ as the state vector, the output of the system is $y = V$, and the input is $u = i$, so the state space equation of the system can be obtained as follows.

Figure 1.
Thevenin equivalent
circuit

$$\dot{x} = Ax + Bu \quad (5)$$

$$y = V_{oc}(S) + V_i + iR_i \quad (6)$$

$$\text{where } A = \begin{bmatrix} 0 & 0 \\ 0 & -\frac{1}{R_s C_s} \end{bmatrix}, B = \begin{bmatrix} \frac{\eta}{C_t} \\ \frac{1}{C_s} \end{bmatrix}.$$

For (5) and (6) discretization, the sampling time interval $T_s = 1$ s, the state model equation obtained by considering the deviation situation is as follows.

$$x_{k+1} = A_d x_k + B_d u_k + w_k \quad (7)$$

$$y_k = V_{oc,k}(S_k) + V_{s,k} + i_k R_k + v_k \quad (8)$$

where x_k is the system state at t_k , y_k is the measurement output of the system; the system input variable at t_k is represented by i_k . That is, the current in the process of battery charging and discharging; $V_{s,k}$ is the polarization reaction voltage of lithium-ion trolley at t_k ; w_k is the process noise at the time of t_k , v_k is the measurement noise.

Σ^w , Σ^v are two independent white Gaussian noise variances. The dynamic transfer matrix and observation matrix after discretization of A and B are as follows.

$$A_d = \begin{bmatrix} 1 & 0 \\ 0 & 1 - \frac{1}{R_s C_s} \end{bmatrix}, B_d = \begin{bmatrix} \frac{\eta}{C_t(k)} \\ \frac{1}{C_s} \end{bmatrix} \quad (9)$$

Eqns. (7) and (8) are the state space equations corresponding to the equivalent circuit model, on which the SOC estimator can be designed. In order to obtain the values of the variables in the model parameters, an improved fitting method is adopted and used in this paper to fit the relationship between SOC and OCV, while the use of the end-voltage exponential fit will further yield the values of capacitance and resistance in the equivalent model. The exact OCV-SOC relationship is shown in Figure 2.

By fitting the relationship between open circuit voltage and SOC, the following expression can be obtained.

$$V_{oc} = 5.4698 + 0.0269S - 0.002S^2 + 1.209e^{-4}S^3 - 6.3072e^{-6}S^4 \quad (10)$$

In this paper, the method of exponential fitting is used to identify the capacitive resistance parameters in Eqns. (7) and (8). The root mean square error and standard deviation obtained using least squares are the smallest of the terms, accurate and closer to the BMS reaction time.

Figure 2.
OCV-SOC relationship
of fast static calibration
method

Through the reasonable analysis of the output equation of the battery, the exponential function fitting method is used in this paper to fit the trend of voltage change in the region of current mutation. Finally, according to the relationship between the fitted variables and the resistance value, the capacitance value C_s and the resistance value R_s in the equivalent circuit model are obtained. In Thevenin equivalent circuit model, current is regarded as input, and the output of the system is as follows.

$$V = V_{oc} + R_i i + R_s i (1 - e^{-t/\tau_1}) \quad (11)$$

Similarly, due to the need of parameter identification, this paper uses exponential function to fit Eqn. (11).

$$V_{out} = k_0 + k_1 e^{-\lambda_1 t} \quad (12)$$

where k_0 , k_1 , λ_1 are the fitting variables, V_{out} and is the output of voltage change.

The fitting result is shown in Figure 3. The blue curve is the voltage curve of the fitting result, and the red curve is the actual measured value during operation. It can be seen from the figure that the change curve of battery voltage predicted by the model is highly consistent with the actual situation, indicating that the identification result can accurately reflect the state change during the operation of the battery.

The exponential fit yields the following values for the variables $k_0 = 3.76229$, $k_1 = -0.06014$, $\lambda_1 = 0.02268$. Then, by fitting the connection between the capacitance and the resistance, the expression for the relationship between capacitance and resistance in the equivalent model can be obtained, as shown in Eqn. (13).

$$\begin{cases} R_s = \frac{k_1}{i} \\ C_s = \frac{1}{\lambda_1 R_s} \\ R_t \approx \frac{\Delta V}{i} \end{cases} \quad (13)$$

Among them, it can be calculated that $R_i = 0.05095 \Omega$, $R_s = 0.3007 \Omega$, $C_s = 124.6459 \Omega$, the result of parameter identification can be brought into Eqns. (14) and (15), and the state space model corresponding to the equivalent circuit model can be obtained as follows.

$$x_{k+1} = A_d x_k + B_d u_k + w_k \quad (14)$$

Figure 3.
Voltage curve of
identification result

$$y_k = V_{oc,k}(S_k) + V_{s,k} + i_k R_k + v_k \quad (15)$$

$$\text{where } A_d = \begin{bmatrix} 1 & 0 \\ 0 & 1 - \frac{1}{R_s C_s} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & -36.4532 \end{bmatrix}, B_d = \begin{bmatrix} \frac{\eta}{C_t(k)} \\ \frac{1}{C_s} \end{bmatrix} = \begin{bmatrix} 0.0014 \\ 0.008 \end{bmatrix}$$

2.3 Establishment of capacity model of lithium-ion battery

The change of the rated capacity of the battery shows the change of its SOH, that is, the prediction of SOH can be made by estimating model of the rated capacity of the battery. Therefore, it is necessary to establish the corresponding model for estimating the battery capacity, that is, the capacity model. Considering that the battery capacity changes in a short period of time are relatively small, the capacity changes can be expressed as follows.

$$C_{k+1} = C_k + r_k \quad (16)$$

where C_k is the rated capacity of the battery at time t_k ; r_k is the process noise of the capacity model at time t_k , which is the Gaussian white noise with mean value of zero and variance of Σ' .

Generally, current and terminal voltage can be measured directly from a battery system. Therefore, in the capacity prediction system, the terminal voltage is chosen as the output variable and the current as the input variable. The output equation of the corresponding equivalent circuit model is also the output equation of the battery capacity model, that is, the above Eqn. (16) is also the output equation of the capacity model.

3. Prediction method based on multi time scale theory

Due to the aging and performance deterioration caused by the use of batteries, the external performance shows the decline of capacity and power. In the energy management of electric vehicle battery, the health status of battery is evaluated by the number of cycles, battery voltage and internal resistance parameters under full saturation state. If any of these variables reach the threshold value, the vehicle battery can be judged to be in dangerous operation (Farjah and Ghanbari, 2020; Han *et al.*, 2014).

In this paper, SOH is calculated by the common judgment method of current research capacity, that is, the ratio of the maximum amount of electricity released by the battery in the use of the vehicle to the factory capacity marked on the nameplate of the vehicle battery, as shown in Eqn. (17).

$$\text{SOH} = \frac{Q_{\text{aged}}}{Q_{\text{new}}} * 100\% \quad (17)$$

As expected SOC in vehicle environment, SOH is also a nonlinear time-varying system. Environmental temperature and humidity, service speed, over discharge and service cycle are all factors that affect the prediction of SOH.

3.1 Multi-time scale estimation

3.1.1 Multi-time scale EKF model transformation. Multi-time scale analysis is based on the establishment of multi-scale theory, which reflects the change of variables in different dimensions and multi-scale research on the research object, with multi-scale characteristics. Compared with the change of the rated capacity of vehicle battery, the SOC of vehicle battery changes more frequently in the use of vehicle battery. Especially in the condition of high current charging and discharging, the driving moment can change a lot. However, since the change of vehicle battery SOH is very slow, there is no obvious change in the initial stage of use, indicating that the time changes of SOC and SOH scale are

different. The error inevitably increases if the SOC projections and the SOH status are studied at the same scale (Hu *et al.*, 2020; Zou *et al.*, 2016; Hua *et al.*, 2015). In order to reduce the deviation and simplify the calculation of the estimator, a multi-time scale estimation method is designed to realize the joint estimation of SOC and SOH of vehicle battery. Establishing macro and micro scales of measurement to estimate the rated capacity of vehicle batteries at the macro scale and at the frequently changing micro time scale. The SOC of the vehicle battery is estimated on, polarization response voltage, as a macroscopic scale variable. Transformation of the established state space model allows to obtain a mathematical model description.

$$x_{k,l+1} = A_d \cdot x_{k,l} + B_d \cdot i_{k,l} + w_{k,l} \quad (18)$$

$$C_{k+1} = C_k + r_k \quad (19)$$

$$y_{k,l} = V_{oc}(S_{k,l}) - V_{sk,l} - i_{k,l} \cdot R_i + v_{k,l} = g(x_{k,l}, i_{k,l}) + v_{k,l} \quad (20)$$

where $x_{k,l} = [S_{k,l} \ V_{sk,l}]$ is the microscale variable of the system at time $t_{k,l} = t_{k,0} + l \cdot T_s$, $0 \leq l \leq L$, L is the time scale separation quantity, $t_{k,0} = t_{k-1,L}$, T_s is the sampling interval time of 1s, k and l are the counting variables of different scales respectively. C_k is the rated capacity of the battery of the system at $t_{k,0}$. $i_{k,l}$ is the input variable, i.e. the current change of vehicle battery at the time of $t_{k,l}$ during driving; $y_{k,l} = V_{k,l}$ is the observed value of the system, that is, the measured value of the vehicle battery terminal voltage at the time of $t_{k,l}$.

3.1.2 Multi time scale EKF algorithm. In the multi-time scale framework, SOC and SOH of vehicle battery are predicted based on EKF. SOC of vehicle battery is observed at micro scale, while SOH is predicted at macro scale. For the convenience of research, EKF_x is used as the micro filter for the state of charge of the battery, EKF_c represents the macro estimation for the capacity of the vehicle battery. Combined with the predicted algorithm block diagram, as shown in Figure 4, it can be seen that SOC and rated capacity of vehicle lithium battery are not

Figure 4.
Block diagram of
vehicle battery SOC
and capacity
estimation based on
multi-time scale EKF

predicted at the same time, and SOC estimation frequency is significantly higher than capacity estimation frequency. It can reduce the error by simplifying the calculation.

The algorithm steps of multi time scale EKF are as follows.

For initial time as $t_{0,0}$ ($k = 0, l = 0$)

(1) Initializing the multiscale EKF.

$$\hat{C}_0 = E[C_0] \quad (21)$$

$$P_0^c = E[(C_0 - \hat{C}_0)(C_0 - \hat{C}_0)^T] \quad (22)$$

$$\hat{x}_{0,0} = E[x_{0,0}] \quad (23)$$

$$P_{0,0}^x = E[(x_{0,0} - \hat{x}_{0,0})(x_{0,0} - \hat{x}_{0,0})^T] \quad (24)$$

For t_k time ($k = 1, 2, \dots$)

(2) Updating the time of EKF_c.

$$\hat{C}_k^- = \hat{C}_{k-1} \quad (25)$$

$$P_k^{c-} = P_{k-1}^c + \Sigma_{k-1}^r \quad (26)$$

For $t_{k-1,l}$ time ($l = 1, 2, \dots, L$)

(3) Updating the time of EKF_x.

$$\hat{x}_{k-1,l}^- = A_d \cdot \hat{x}_{k-1,l-1}^- + B_d \cdot i_{k-1,l} \quad (27)$$

$$P_{k-1}^{x-} = A_d \cdot P_{k-1,l-1}^x \cdot A_d^T + \Sigma_{k-1,l-1}^w \quad (28)$$

(4) Updating measurement of EKF_x.

$$K_{k-1,l}^x = P_{k-1,l}^{x-} \cdot C_{k-1,l}^x \cdot [C_{k-1,l}^x \cdot P_{k-1,l}^{x-} \cdot C_{k-1,l}^{xT} + \Sigma_{k-1,l}^v]^{-1} \quad (29)$$

$$\hat{x}_{k-1,l} = \hat{x}_{k-1,l}^- + K_{k-1,l}^x \cdot [y_{k-1,l} - g(\hat{x}_{k-1,l}^-, i_{k-1,l})] \quad (30)$$

$$P_{k-1,l}^x = [I - K_{k-1,l}^x \cdot C_{k-1,l}^x] \cdot P_{k-1,l}^{x-} \quad (31)$$

(5) Extracting battery status.

$$S_{k-1,l} = [1 \ 0] \cdot \hat{x}_{k-1,l} \quad (32)$$

(6) Calculating time series.

When $l = 1, 2, \dots, L$, cycling through steps (3) to (5) to get $\hat{x}_{k-1,l}$ and $P_{k-1,l}^x$.

(7) Converting timescale.

$$\hat{x}_{k,0} = \hat{x}_{k-1,L} \quad (33)$$

$$P_{k,0}^x = P_{k-1,L}^x \quad (34)$$

$$y_{k,0} = y_{k-1,L} \quad (35)$$

$$i_{k,0} = i_{k-1,L} \quad (36)$$

For $t_k (k = 1, 2, \dots)$

(8) Updating measurement of EKF.

$$K_k^c = P_k^{c-} \cdot C_k^{cT} \cdot [C_k^c \cdot P_k^{c-} \cdot C_k^{cT} + \Sigma_k^v] \quad (37)$$

$$\hat{C}_k = \hat{C}_k^- + K_k^c \cdot [\hat{x}_{k,0} - \hat{x}_{k-1,L}] \quad (38)$$

$$P_k^c = [I - K_k^c \cdot C_k^c] \cdot P_k^{c-} \quad (39)$$

(9) Extracting of the rated capacity of battery.

$$C_k = \hat{C}_k \quad (40)$$

where $\hat{C}_k$ is an estimate of C_k ; $\hat{x}_{k-1,L}$ is an estimate of $x_{k-1,L}$; $E[*]$ is the formula for arithmetic mean; P_k^c is the capacity forecast variance matrix; $P_{k,l}^x$ is the state estimation error variance matrix; $\hat{C}_k^-$ is the capacity prior estimation; $\hat{x}_{k,l}^-$ is the state prior estimation value; $P_{k,l}^{x-}$ is the prior estimation of state estimation error variance; $K_{k,l}^x$ is the feedback gain matrix of state estimation and K_k^c is the feedback gain matrix of capacity estimation.

Matrices C_k^c and C_k^d can be expressed as

$$C_k^c = \frac{\partial g(\hat{x}_{k,0}, i_{k-1,L})}{\partial C_k} \Big|_{C_k = \hat{C}_k} = \frac{\partial g(\hat{x}_{k,0}, i_{k-1,L})}{\partial \hat{C}_k^-} + \frac{\partial g(\hat{x}_{k,0}, i_{k-1,L})}{\partial \hat{x}_{k,0}} * \frac{d\hat{x}_{k,0}}{d\hat{C}_k^-} \quad (41)$$

$$C_k^d = \frac{\partial g(x, i_{k-1,L})}{\partial x} \Big|_{x = \hat{x}_{k,0}} = \frac{\partial g(\hat{x}_{k,0}, i_{k-1,L})}{\partial \hat{x}_{k,0}} * \frac{d\hat{x}_{k,0}}{d\hat{C}_k^-} \quad (42)$$

4. Comparative analysis of experiments and results

4.1 Algorithm verification under vehicle test condition

In this paper, new European driving cycle (NEDC), New York city cycle (NYCC) and urban dynameter driving schedule (UDDS) are used to verify the joint estimation algorithm under different vehicle states. The operation of the three conditions is shown in [Figure 5](#).

4.2 Analysis of experimental results

During the experiment, the initial SOC value of vehicle battery is 0.8, and the rated capacity of new battery nameplate is 27 Ah (SOH = 0.93). In order to test the robustness of the designed estimator when the initial value is biased, the SOC initial value of the designed estimator is set as 0.9, the initial capacity value is 26.3 Ah (SOH = 0.912). The scale variable of multi time scale algorithm L is 100. On the macro time scale, time and measurement are updated every $L \cdot T_s$, the variable data used in vehicle battery SOC measurement update is estimated in micro EKF.

Based on advisor simulation platform, the simulation results of battery are shown in [Figure 6](#).

(a) Represents the simulation results under NEDC condition. The first block diagram shows the end voltage and current variation curve of vehicle battery, the second block diagram represents the estimated battery SOC estimation value, and in the third block diagram, the blue curve represents the end voltage curve of vehicle battery unit, and the red

Figure 5.
Operation diagram of
three working
conditions

(a)

(b)

(c)

Figure 6.
Simulation results
under three working
conditions

curve represents the error change. The fourth block diagram shows the change of capacity and deviation curve of SOH. It can be seen from the second block diagram that the estimation error is less than 0.3%. In the initial stage of 200s, due to setting the initial value of deviation from the actual value, the estimation result error is obvious, and the deviation gradually decreases with the increase of operation time. In the fourth block diagram, in the rated capacity variation curve, there is a large deviation between the estimated capacity and the actual value at the initial moment, and the error gradually converges with time, and the estimation accuracy deviation is always kept in a small range.

(b) Represents the simulation results under NYCC condition. The first block diagram is voltage and current curve, the second block diagram is SOC and single voltage, and the second block diagram is battery operating temperature. The estimated curve in the figure always coincides with the actual measured result. The second block diagram shows that the accuracy of SOC and capacity estimation of vehicle battery has practical engineering application.

(c) Represents the simulation results under UDDS condition. The three block diagrams in the figure are the same as those of (b). The diagram shows that the loop test is stable.

5. Conclusion

In this paper, a joint estimation method of SOC and SOH based on multi time scale EKF algorithm is proposed. The multi time scale EKF algorithm is analyzed, in which the macro EKF is used to estimate the rated capacity and the micro EKF is used to estimate the SOC. A multi-scale algorithm estimator with high computational frequency and small computational size is designed, and the rationality of the algorithm is verified by simulation under working conditions. As can be seen from the experimental simulation curves, the multi-timescale EKF algorithm can be implemented very accurately to measure the lithium-ion battery status and remaining life of the vehicle.

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