A Novel Adaptive SOC Estimation Method for a Series-connected Lithium-ion Battery Pack Under Fast-varying Environment Temperature

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Abstract
This paper proposes a model-based state-of-charge (SOC) estimation method for a series-connected battery pack under fast-varying environment temperature. For accurately evaluating the SOC of the battery pack equipped with passive balance control, the relationship of battery pack and in-pack cell in the available capacity is analyzed. A filtering process is applied to select the alterable reference cell (ARC) for supporting the modeling framework of SOC estimation. An adaptive SOC estimator is presented by using an optimized recursive least squares algorithm to identify all cells parameters, and using an adaptive extended Kalman filter algorithm (AEKF) to estimate the pack generalized SOC in real-time. Furthermore, a bias correction approach is developed to compensate the cell available capacity at low temperature based on the cell resistance of off-line identification and the open-circuit voltage (OCV) of on-line estimation. The experimental verification is conducted through the modified Federal Urban Driving Schedule (FUDS) cycles with environment temperature varying from 25°C to -35°C. Results show that the accuracy of the proposed SOC estimation method is considerably high, and the correction approach can compensate the cell available capacity effectively with acceptable error.

Keywords: lithium-ion battery pack, state-of-charge estimation, fast-varying environment temperature, passive balance control.

Nomenclature

Abbreviation

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>AEKF</td>
<td>Adaptive Extended Kalman Filter</td>
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<tr>
<td>ARC</td>
<td>Alterable Reference Cell</td>
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<tr>
<td>BMS</td>
<td>Battery Management System</td>
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<tr>
<td>EV</td>
<td>Electric Vehicle</td>
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<tr>
<td>FUDS</td>
<td>Federal Urban Driving Schedule</td>
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<tr>
<td>OCV</td>
<td>Open-Circuit Voltage</td>
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<tr>
<td>ODCR</td>
<td>Overall Direct-Current Resistance</td>
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PHEV       | Plug-in Hybrid Electric Vehicle |
RMSE       | Root Mean Square Error |
SOC        | State-of-Charge |
VFFRLS     | Recursive Least Squares Algorithm with Variable Forgetting Factor |

Symbols

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
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<tbody>
<tr>
<td>Ah</td>
<td>Ampere-Hour</td>
</tr>
<tr>
<td>Nₙ</td>
<td>The number of series-connected cells</td>
</tr>
<tr>
<td>k</td>
<td>k-th time-step</td>
</tr>
<tr>
<td>n</td>
<td>n-th in-pack cell</td>
</tr>
<tr>
<td>r</td>
<td>r-th cell is selected as ARC</td>
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1. Introduction

In recent years, with the continuous development of power electronics technologies, lithium-ion batteries have been obtained extensive application in various electrical systems and hybrid power systems playing the key role of energy storage [1]. For reducing the air pollution caused by automobile emissions and making the better utilization of renewable energy, one common application of lithium-ion batteries is to be the main energy source in a plug-in hybrid electric vehicle (PHEV) [2]. In practical use, tens or hundreds battery cells are put together to form battery pack by series and parallel connection for meeting the requirements of high power and large capability. As the results of the unavoidable error of manufacturing process and the influence of varying environment temperature, the characteristic of in-pack cells are inconsistent, which lead to the battery pack SOC differ from each cell SOC. On the other hand, the battery pack SOC is also depended on the balance control strategy of battery management system (BMS) [3].

The battery pack SOC is used in indicating the driving range of electric vehicles (EV) and PHEV. A number of great efforts have been made to improve the accuracy of SOC estimation for battery pack. Sun, Xiong et al.[4] built up a reference model for the initialization and prior estimation of all cells SOC with AEKF algorithm, and developed a neural network.
based algorithm for the determination of the bias function of each cell. Zheng et al. [5] considered the inconsistency of in-pack cells SOC, as well as cells internal resistance, and accurately predicted the mean SOC of pack and the individual SOC of cell at every sample step by the application of mean-difference model and EKF algorithm. Both the two SOC estimation methods mentioned above utilized the reference model to track the entirely dynamic behavior of pack, and then employed different approaches to correct SOC for every cell. But these studies did not clearly define the battery pack SOC or did not consider the influence of equalization control on pack SOC. Moreover, the accuracy and reliability of the methods in those studies are verified only at room temperature.

To enhance the environmental adaptability and reliability of EV and PHEV BMS under fast-varying environment temperature, this paper presents an adaptive SOC estimation method for a series-connected battery pack. A novel modeling framework of SOC estimation is developed and the alterable reference cell (ARC) is selected to support the modeling framework. For meeting the demands of low computational complexity and high accurate SOC estimation, an VFRLS-AEKF based SOC estimator is set up. In addition, a bias correction approach is presented to compensate the available capacity of in-pack cell at low temperature. At last, a modified FUDS test cycles is loaded on the battery pack under fast-varying environment temperature for experimental verification.

2. Parametric Modeling

2.1 The SOC of the battery pack equipped with passive balance control

2.1.1 Definition for the SOC of battery cell

The available capacity and the SOC of in-pack cell are denoted by $Ca_n$ and $SOC_{cell,n}$, respectively, where $n \in [1,2,...,N]$. $SOC_{cell,n}$ is usually expressed as the ratio of the remaining available capacity to $Ca_n$, given by:

$$SOC_{cell,n}(t) = SOC_{cell,n}(t_0) + \frac{\eta o \int_{t_0}^{t} I(\tau) d\tau}{Ca_n}$$

(1)

where $\eta o$ represents the coulomb efficiency, $I(\tau)$ denotes the value of current which is negative for discharge or positive for charge.

As the Eq.1 shows, the calculation result of $SOC_{cell,n}$ is directly related to the value of $Ca_n$, which is changing with varying cell temperature. However, it is time-consuming to experimentally calibrate $Ca_n$ for all in-pack cells at different temperatures due to the inconsistent capacity characteristic of each cell.

This paper defines $SOC_{cell,n}$ as the generalized SOC. In the definition of the generalized SOC, $Ca_n$ is treated as nominal capacity, that is:

$$Ca_1 = Ca_2 = ... = Ca_N = Ca_{nominal}$$

(2)

According to the Eq.1, as for the battery pack with series connection, because of the same output current of in-pack cells, the inconsistency of $SOC_{cell,n}$ is depended on the non-uniform initial remaining capacities and different coulomb efficiency of cells.

2.1.2 Analyzing for the SOC of battery pack

![Figure 1 Fully charged and empty stage of the battery pack equipped with passive balance controller](image)

The passive balance control is the essential equalization approach applied in the BMS of EV and PHEV. Fig.1 displays the end of being fully charged and discharged of a series-connected battery pack equipped with passive balance control. The action of equalization causes the remaining capacity of in-pack cells are equal after being fully charged for the first time, even if the initial capacity of cells are different before packing. Therefore, the generalized SOC of the battery pack, denoted by $SOC_{pack}$, is obviously equal to the generalized SOC of each in-pack cell, shown as:

$$SOC_{pack} = SOC_{cell,1} = SOC_{cell,2} = ... = SOC_{cell,N}$$

(3)

The application of the generalized SOC is meaningful as the majority of EV and PHEV BMS limit battery cell to operate within the design range of 5%~100% nominal capacity.

2.2 Modeling for pack SOC estimation

2.2.1 Cell filtering process

During battery pack operation, the temperature of in-pack cells are uneven caused by their inconsistent heat dissipation and battery characteristics. The non-uniform temperature profile in battery pack makes the
terminal voltage of in-pack cell differ from each other, even though all cells generalized SOC are same. Consequently, it is impossible to select only one fixed reference cell from battery pack for SOC estimation like the method of Ref.[6] since the cell with the lowest terminal voltage is varied. To solve this problem, a filtering approach is developed by selecting the cell with the lowest moving average voltage as the alterable reference cell (ARC). This filtering approach is expressed as Eq.4 and Eq.5:

$$V_{d,n}(k) = \frac{1}{M} \sum_{j=k-(M-1)}^{k} V_{t,n}(j)$$  \hspace{1cm} (4)

$$ARC = \left\{ r \mid V_{d,n}(k) = \text{Minimum}\{V_{d,n}(k)\} \right\}$$  \hspace{1cm} (5)

where the moving average voltage of in-pack cell is denoted by $V_{d,n}$, $V_{t,n}$ denotes the terminal voltage of cell, $M$ is the window length of moving average, $V_{d,n}$ is the minimum value of $V_{d,n}$, while the subscript $n$ indicates the n-th cell in battery pack, the value of $r$ indicates that the r-th cell is the selected ARC, $k$ is the discrete sampling time-step.

For a series-connected battery pack, the ARC is the most possible first one to reach the limited discharge voltage during discharge. Which means the parameter of ARC can best represent the battery pack characteristics. Thus, it is reasonable to estimate $SOC_{\text{pack}}$ by tracking the SOC of ARC.

### 2.2.2 Modeling for in-pack cell

The Thevenin equivalent circuit model is employed for battery cell modeling and SOC estimation. The electrical behavior of in-pack cell can be expressed by Eq.6:

$$\begin{cases} 
\dot{V}_{t,n} = -\frac{1}{R_{i,n}C_{i,n}} V_{t,n} + \frac{1}{C_{i,n}} I \\
V_{t,n} = OCV_{n} - V_{r,n} - IR_{0,n}
\end{cases}$$  \hspace{1cm} (6)

where the voltage source of cell is denoted by $OCV_{n}$, $V_{t,n}$ denotes the diffusion voltage over the RC network, $R_{i,n}$ and $C_{i,n}$ represents the equivalent ohmic resistance, while $R_{0,n}$ and $C_{i,n}$ represent the equivalent polarization resistance and polarization capacitance respectively.

For battery cells, the empirical relationship between OCV and the generalized SOC is found through battery test and modeled by using five-order polynomial, which can be written as:

$$g_{n}(s_{n}) = OCV_{n}(s_{n}) = P_{n}s_{n}^{T}$$  \hspace{1cm} (7)

$$P_{n} = [p_{0,n}, p_{1,n}, p_{2,n}, p_{3,n}, p_{4,n}, p_{5,n}]$$

$$S_{n} = [s_{n}, s_{n}^{2}, s_{n}^{3}, s_{n}^{4}, s_{n}^{5}]$$

where $s_{n} \in [0,1]$ represents the value of $SOC_{\text{ref,n}}$, the constant parameter set $P_{n}$ of all cells are identified offline.

Additionally, the combined mode [7] is utilized for supporting the cell available capacity correction, which is shown as follows:

$$V_{t,n} = OCV_{d,n}(s_{n}) + VR_{p,n}$$

$$OCV_{d,n}(s_{n}) = K_{0,n} - \frac{K_{1,n}}{s_{n}} - K_{2,n}s_{n} + K_{3,n} \ln(s_{n}) + K_{4,n} \ln(1 - s_{n})$$  \hspace{1cm} (8)

where $V_{t,n}$ is divide into two part: one part denoted $OCV_{d,n}(s_{n})$, and another denoted $VR_{p,n}$. $OCV_{d,n}(s_{n})$ can well represent cell OCV and it also contains the voltage drop part of slow polarization response which is ignored in Thevenin model. $VR_{p,n}$ represents the voltage drop part of fast dynamic response. The time-varying parameter set $\theta_{\text{combined,n}}$ of all cells are identified online.

### 3. Adaptive Model-based SOC estimation

#### 3.1 VFFRLS algorithm for online identification

The recursive least square (RLS) algorithm is wildly utilized to update the slow-varying parameter of the equivalent model for battery cell. However, the model parameter of in-pack cell would be fast-varying when battery pack operating under fast-varying temperature environment. The performance of RLS algorithm to track varying parameter is strongly depended on the forgetting factor $\lambda$, which is usually set to a fixed value between 0.999 and 1. This paper used an optimized RLS algorithm with variable forgetting factor (VFFRLS) [8] to online identify the fast-varying parameter of the in-pack cell.

The calculation process of the variable forgetting factor $\lambda(k)$ in the RLS algorithm is derived as:

$$\alpha(k) = \text{sign}\left[\epsilon_{n}(k)e_{n}(k-1)\right]$$  \hspace{1cm} (9)

$$\beta(k) = \left[1 + \rho \alpha(k) \times \text{sign}\left[\frac{\varphi}{(k)K_{n}(k)}\right]\right] \beta(k-1)$$  \hspace{1cm} (10)

$$\lambda(k) = 1 - \beta(k)$$  \hspace{1cm} (11)

where $\epsilon_{n}(k)$ and $K_{n}(k)$ is the estimation error and the gain of RLS respectively. $\text{sign}$ denotes the sign function which returns -1 or 1, $\rho$ is a positive constants for adjusting $\lambda(k)$, $\varphi^{T}(k)$ is the transpose of the input vector of RLS.

#### 3.2 AEKF algorithm for SOC estimation

The extended Kalman filter (EKF) algorithm deals with the nonlinearity of $g(s)$ with first-order Taylor accuracy and has reasonably good performance for the SOC estimation of lithium-ion cells with nickel manganese cobalt oxide. For improving the robustness of SOC estimator to the process noise and measurement noise, this paper uses an adaptive extended Kalman filter (AEKF) algorithm [4] for SOC estimation.
The state matrix $A(k)$ and measurement matrix $C(k)$ of the state space based on the Thevenin model are given:

$$A(k) = \begin{bmatrix} 1 & 0 \\ 0 & \exp\left(-T / (R_c(k)C_{tr}(k))\right) \end{bmatrix}$$  \hspace{1cm} (12)$$

$$C(k) = \begin{bmatrix} \tilde{g}(\text{SOC}(k)) \\ \tilde{g}(\text{SOC}(k)) \end{bmatrix}$$  \hspace{1cm} (13)$$

Different from the original EKF algorithm, the unique adaptive noise covariance matching law of AEKF algorithm is expressed as follows:

$$H(k) = \frac{1}{L} \sum_{i=k-L+1}^{k} e(i)e(i)^T$$  \hspace{1cm} (14)$$

$$Q(k) = K(k)H(k)K(k)^T$$  \hspace{1cm} (15)$$

$$R(k) = H(k) - C(k)P^*(k)C(k)$$  \hspace{1cm} (16)$$

where $e(i)$ is the estimation error at $i$-th time-step, $K(k)$ is the Kalman gain, $P^*(k)$ is the prior estimation of error covariance matrix, the independent covariance matrices of the process noise and measurement noise are denoted by $Q(k)$ and $R(k)$ respectively. $L$ is the widow length of covariance matching law.

3.3 VFFRLS-AEKF based SOC estimator

This paper builds up a VFFRLS-AEKF based SOC estimator for the battery pack. Fig.2 illustrates the framework of SOC estimation method, including the schematic of both the adaptive SOC estimator and the available capacity correction approach. The VFFRLS is used to update the model parameter of ARC and other in-pack cells at micro and macro time-scale respectively. That is, the ARC’s parameters are identified at each sampling time-step. But for other cells, the online identification only occurs continuously at $L_1$ time-steps every $L_2$ sampling interval. $L_2$ represents the level of macro time-scale. $L(k)$ is the counter for time-scale conversion. The terminal voltage, current, as well as the model parameters of ARC are the inputs of AEKF for SOC estimation.

Here, $V_{\text{min}}$ denotes the limited cell discharge voltage $(3V)$. $C_{\text{correct}}$ denotes the corrected pack available capacity. $\Delta U$ denotes the slow polarization response part of ARC dynamics which is identified on-line with VFFRLS, $R_{\text{DC}}$ denotes the overall direct-current resistance (ODCR) which is needed to be off-line identified according to the data obtained by a series of systematic direct-current pulse discharge tests under different temperatures and discharge current-rate.

Based on $\Delta U_p$ and the function of $R_{\text{DC}}$, we develop a bias correction approach to compensate the pack available capacity in real-time.

![Flowchart of the adaptive SOC estimation method for the series-connected battery pack](image)

Fig.2 The flowchart of the adaptive SOC estimation method for the series-connected battery pack

4. Verification and Discussion

4.1 Experiment

To verify the effectiveness of the proposed method, a battery test bench is built up and a modified FUDS test cycle is designed. The test bench is composed of a series-connected battery pack, a data acquisition...
device with the sampling frequency of 10HZ, a NEWARE BTS4000 to control the discharge of battery pack, a thermal chamber to regulate the environment temperature varying from 25°C to -35°C. The battery pack consists of four LiNi₀.₅Co₀.₅Mn₁O₂ battery cells with the nominal capacity of 10Ah. For avoiding the harm of charging battery at the temperature below 0°C, all the charge steps of FUDS are deleted in the test cycle. The voltage and current profiles of in-pack cells are plotted in Fig.3(a) and (b). The variation trend of cell temperature and environment temperature are depicted in Fig3(c).

Fig.3 The measured profiles of in-pack cell under the modified FUDS: (a) voltage;(b) current;(c) temperature

4.2 Results and discussion

The model parameter of four in-pack cells are updated in the SOC estimator by using VFFRLS, and the identification results of ohmic resistance and polarization resistance are plotted in Fig.4. For the Thévenin model, comparing with the variation trend of cell ohmic resistance, cell polarization resistance is more sensitive to the changing of temperature. Fig.5 contrasts the absolute error of VFFRLS and RLS during the identification of ARC parameters. It shows that VFFRLS has better tracking performance with root mean square error (RMSE) of 4.3mv and maximum error less than 100mv.

Fig.4 Results of parameter identification for in-pack cell

Fig.5 The identification errors of VFFRLS for ARC

Fig.6 Results of SOC estimation for battery pack

The results of bias correction for in-pack cell available capacity are plotted in Fig.7. Where the 2C-rate available capacity denotes the cell maximum capacity discharged with 2C-rate under present temperature condition. At the last one time-step of test cycles, under the loading condition of 20A (the
equivalent 2C-rate of 10Ah battery cell), 1-th cell having the lowest terminal voltage of 3.045V is selected as the ARC through the filtering process. Since the voltage of ARC is very close to the limited discharge voltage of 3V at the end of test cycles, it can be considered that the final discharged capacity is the actual 2C-rate available capacity of battery pack. As Fig. 7 shows, the actual 2C-rate available capacity of battery pack is 6.168Ah and the corrected 2C-rate available capacity of ARC is 5.990Ah. Which proves that the proposed capacity correction approach is effectiveness with the acceptable error of 2.89%.

5. Conclusions

According to the definition of the generalized SOC, all cells SOC are equal in the series-connected battery pack equipped with passive balance control. In this paper, the pack SOC estimation is implemented by tracking the SOC of ARC. A filtering approach is developed for selecting the ARC. Based on the Thevenin model of ARC, the VFFRLS algorithm and AEKF algorithm are employed to establish a novel adaptive SOC estimator. In addition, based on the combined mode, the in-pack cell OCV is estimated online with VFFRLS for available capacity correction. Experimental results verify that the proposed SOC estimation method can accurately estimated the battery pack SOC with RMSE of 0.56% under the fast-varying environment temperature changed from 25°C to -35°C. Moreover, a novel bias correction approach is presented to compensate the available capacity of in-pack cell with the falling temperature.

Further research on improving the accuracy of available capacity correction approach for battery pack and evaluating the actual battery pack SOC will be done by using the method proposed in this paper.

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Reference