Dual time-scale co-estimation of state-of-charge and state-of-health for lithium-ion battery pack with passive balance control over whole lifespan based on particle filter

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Abstract—Battery management system (BMS), as the key component in electric vehicles (EVs), takes the responsibility of state-monitoring and safety-protection for the battery pack. State of charge (SOC) and state of health (SOH) are the most two important parameters that need to be estimated accurately by battery management system (BMS). Because these parameters cannot be measured directly, how to obtain these parameters with high precision has posed a great challenge, especially under the environment of electric vehicles’ highly dynamic operation [2].

So far, most researches focus on just one state estimation of the battery on cell-level. However, given the fact that SOC and SOH are strongly correlated with each other, it is more suitable to incorporate them under a systematic co-estimation framework to realize higher fidelity estimation results [3].

1. INTRODUCTION

To ensure safety of electric vehicles (EVs) and optimize the energy management strategy, it is necessary to realize comprehensive, effective and elaborate monitoring of power battery packs during vehicle operation [1]. State of charge (SOC) and state of health (SOH) are the most two important parameters that need to be estimated accurately by battery management system (BMS). Because these parameters cannot be measured directly, how to obtain these parameters with high precision has posed a great challenge, especially under the environment of electric vehicles’ highly dynamic operation [2].
The main focus of this paper is to establish a systematic framework for SOC and SOH co-estimation of lithium-ion battery pack with passive balance control in electric vehicles, which is accurate and robust under different levels of degradation.

2. DEFINITION OF SOC AND SOH FOR LITHIUM-ION BATTERY PACK WITH PASSIVE BALANCE CONTROL

Battery pack used in EVs usually consists of hundreds of battery cells in series or in parallel. In this paper, we focus on the series topology. In the battery pack, the voltage, capacity, resistance and SOC of different battery cells may differ from each other due to the manufacturing inconsistency, degradation and distinct working environment. This may shorten the battery pack’s service life. Therefore, current BMS usually adopts passive balance control to ensure that battery cells in one battery pack share similar parameters and performance.

The definition of capacity for battery pack is the total ampere-hours drawn from the fully charged cell in the battery pack until one of the cells in the pack is fully discharged. The formula is [4]:

$$C_{pack} = \min_{i \geq 0} (SOC_i \cdot C_i) + \min_{j \geq 1} (1 - SOC_j \cdot C_j)$$

where $C_{pack}$ represents the pack capacity, $SOC_i$ and $C_i$ represent the SOC and capacity of the $i$th battery cell respectively.

Therefore, SOC for the battery pack can be defined as the ratio of the minimum remaining capacity to the pack capacity, which can be expressed as:

$$SOC_{pack} = \frac{\min_{i \geq 0} (SOC_i \cdot C_i)}{C_{pack}}$$

where $SOC_{pack}$ represents the pack SOC.

For the series battery pack with passive control, all battery cells SOC will be balanced to the same value at initial. Thus, battery cell with minimum capacity will be the first to discharge to fully-discharged state. Therefore capacity and SOC for the series battery pack with passive balance can be defined as:

$$C_{pack} = C_{min \_cell} = \min_{i \geq 0} (C_i)$$

$$SOC_{pack} = SOC_{min \_cell} = SOC(0) - \int \frac{n_L(t) \cdot dt}{C_{min \_cell}}$$

where $C_{min \_cell}$ and $SOC_{min \_cell}$ represent the capacity and SOC for the battery cell with minimum capacity.

Based on above analysis, SOH for the investigated battery pack can be expressed as:

$$SOH_{pack} = \min_{i \geq 0} (SOH_i)$$

3. BATTERY EXPERIMENT INTRODUCTION

The battery test data are generated in the test bench consisting of an Arbin BT2000 tester, a thermal chamber, a computer for user-machine interface and a switchboard for cable connection. The voltage, current, temperature of each cell is recorded at the sampling time of 10Hz. The tested batteries were 8 LiNMC battery cells with 0.94Ah nominal capacity, 3.7V nominal voltage. Each cell experienced impedance test and characterization tests (including static capacity test, hybrid pulse test, resistance test, dynamic stress test (DST) and federal urban dynamic schedule (FUDS) test) under 22℃ in different levels of degradation. More details about the battery experiment are available in Ref.[5].

4. DUAL-TIMESCALE CO-ESTIMATION OF SOC AND SOH ALGORITHM

4.1 Battery model

The first-order RC equivalent circuit model (ECM), as shown in Fig.1, is widely adopted to depict lithium-ion battery dynamic characteristics due to its good balance between simplicity and accuracy. It
is comprised of an open circuit voltage (OCV), an ohmic resistance $R_o$ and a RC (polarization resistance $R_p$ and polarization capacitance $C_p$) network [6].

![Fig.1 First-order RC equivalent circuit model for the battery](image)

According to Kirchhoff’s law, the discretized state equation for the first-order RC ECM can be expressed as [7]:

$$v_p(k + 1) = \frac{\exp\left(-\frac{\Delta t}{R_p C_p}\right)}{0 \to 1} v_p(k)_{SOC(k)} + \left(1 - \exp\left(-\frac{\Delta t}{R_p C_p}\right)\right) \frac{i_b(k)}{3600 C_{batt}}$$

where $v_p$ represents the voltage across the RC network, $i_b$ represents incitation current, $C_{batt}$ represents battery capacity, $v_b$ represents terminal voltage, $\Delta t$ denotes sampling period, $\eta_{batt}$ is coulomb efficiency.

The model’s output equation can be expressed as:

$$v_b = OCV - v_p - i_b R_o$$

(7)

### 4.2 Importance of SOH update

As the battery ages, its parameters like capacity and resistance will change accordingly. If relevant parameters are not updated accordingly, the battery model’s accuracy will decrease seriously. Fig.2 shows the voltage response error at different aging states if the voltage response is generated using battery parameters at initial state.

It can be seen from Fig.2 that as the battery ages, the model’s error is increasing. Based on analytical analysis, when the voltage response error exceeds specific threshold, the model parameters need to be updated. Possible trigger condition may include instant voltage error or average voltage error within specific time span. Trigger condition and its corresponding threshold can be adjusted according to application scenario.

![Fig.2 Voltage response error at different aging states](image)

### 4.3 Particle filter

In this paper, we use particle filter to conduct state estimation. For state estimation with Gaussian noise, Kalman filter is an effective method. But in most cases, state noise and measurement noise don’t satisfy Gaussian distribution, which limits Kalman filter’s application scope in real scenario. Based on Monte Carlo sampling method, particle filter can approximate any probability density function of noise using a set of particles. According to Bayesian law, particle filter realizes posteriori probability density estimation of states by continuously updating particles’ location. In addition, each particle has a
corresponding weight, which is defined as the similarity between estimated output and measured output. Detailed algorithm of particle filter can be found in Ref.[8].

4.4 Cell-level co-estimation of SOC and SOH

Increasing voltage response error comes from parameters variation as battery ages. In order to improve SOC and SOH estimation, a dual time-scale estimation framework is proposed, as shown in Fig.3. When model error increases to a certain level, SOH estimator will be triggered. For the offline parameter calibration and SOH estimation, this paper uses forth-order state estimation based on particle filter and the state vector is [9]:

\[
x = [\text{SOC} \ v_p \ \frac{1}{v_{\text{batt}}}]^T
\]

Corresponding state estimation can be expressed as:

\[
x(k+1) =
\begin{bmatrix}
1 & 0 & 0 & -\frac{c}{\text{SOC}} \cdot \Delta t \cdot i_e(k) \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix}
x(k) +
\begin{bmatrix}
0 \\
0 \\
R_p(1 - e^{-\frac{\Delta t}{R_p C_p}}) \\
0
\end{bmatrix}i_e(k)
\]

Output equation is:

\[
y(k) = v_p(k) = f_{\text{OCV}}(\text{SOC}) - v_p(k) - R_s i_e(k)
\]

where \(f_{\text{OCV}}(\text{SOC})\) represents the function that maps SOC to OCV. Based on the above equations, parameters in state vector can be traced using particle filter.

In addition, when the model error is beneath a certain level, SOH estimator will not be triggered and second-order state estimation will be applied, where state vector is [10]:

\[
x = [v_p \ \text{SOC}]^T
\]

By transforming Eq.(6), corresponding state equation can be expressed as:

![Fig.3 Cell-level co-estimation of SOC and SOH framework](image)
\[ x(k + 1) = \left( \exp \left( -\frac{\Delta t}{R_p C_p} \right) \right)^k x(k) + \left( 1 - \exp \left( -\frac{\Delta t}{R_p C_p} \right) \right) R_s + \frac{\eta_{bat} \Delta t}{3600 C_{bat}} i_b(k) \] (12)

The output equation of second-order state estimation is the same as that of forth-order estimation. By applying particle filter, SOC estimation can be realized in real-time.

4.5 Pack-level co-estimation of SOC and SOH
Because SOC changes fast while SOH has slow varying property, this paper presents a dual-timescale co-estimation framework where SOC is estimated online while SOH is updated offline.

The proposed estimation framework, as shown in Fig.4, includes two parts. The first part is the long timescale SOH estimator. When vehicle is at stop for a long time during night, the estimator will extract the past day’s driving data and conduct above cell-level SOC and SOH co-estimation for all cells. Then the battery with minimum capacity will be found. The second part is the real-time SOC estimator. As defined in previous section, SOC of the battery pack is SOC of the battery cell with minimum capacity. Therefore, we can apply second-order state estimation to realize real-time trace of SOC for battery pack.

To realize above estimation framework, BMS needs to save the current and voltage data of all battery cells. When BMS is free and the trigger condition of SOH estimator is satisfied, co-estimation of SOC and SOH will be conducted for all cells. Then by capacity screening, battery cell with minimum capacity can be found and pack’s SOH can be calculated. Because battery resistance and capacity change very slowly, they can be regarded as unchanged during short time period. Thus SOH estimator can be triggered every several weeks (In previous section, the trigger condition is voltage error, but for simplicity, fixed trigger interval is much simpler and is preferred here), which gives BMS enough time to conduct SOH estimation. SOC estimation of battery pack can be realized by focusing on the battery cell with minimum capacity. Because only one cell is needed to realize real-time SOC estimation, the computational burden is greatly lightened.

5. VERIFICATION OF PROPOSED ALGORITHM
Although the proposed algorithm is for battery pack, but according to the SOC and SOH definition for the series battery pack with passive balance control, pack’s states equal to the states of cell with minimum capacity. Therefore, algorithm verification only needs to be conducted at cell level.

Fig.5 plots the co-estimation result when battery is at fresh state. It can be seen that when the initial capacity guess is 10% above the real value, the capacity estimation finally converges to 0.952Ah, whose deviation is only around 3% from the true value. And the SOC estimation error can be controlled within 2.6% (Here only SOC above 20% is considered because battery in EVs seldom deeply
discharged). In addition, when the initial capacity is 10% below the real value, capacity estimation value converges to 0.920Ah, whose estimation error is only 0.4%. Corresponding SOC error can be controlled within 0.4%. Above results show that the proposed co-estimation algorithm is effective when battery is fresh.

![Fig.5 Co-estimation result when battery is fresh](image)

(a)Initial capacity guess is 10% above real value (b)Initial capacity guess is 10% below real value

To further verify the effectiveness and accuracy of the proposed algorithm, Fig.6 demonstrates the estimation result when the battery has undergone 6 rounds aging cycles. It can be seen that when initial capacity guess has ±10% deviation from real value, the capacity estimation error can be beneath 2.5%. SOC estimation error can be controlled within 3% if fluctuation at initial stage is ignored.

![Fig.6 Co-estimation result when battery has undergone 6 rounds aging cycles](image)

(a)Initial capacity guess is 10% above real value (b)Initial capacity guess is 10% below real value

Fig.7 plots the SOH estimation result over the battery’s whole lifespan. It can be seen that the estimation error can be controlled within 3% when initial capacity guess is set as 10% deviation from real value.

![Fig.7 Capacity/SOH estimation result over battery’s whole lifespan](image)

(a)Capacity estimation result (b)SOH estimation result (c)SOH estimation error
To further explicit the importance of SOH update to SOC estimation, Fig.8 compares the SOC estimation result with un-updated and updated (capacity and resistance is updated) for the battery which has undergone 8 rounds aging cycles. It can be seen that if the battery parameters are not updated, SOC error is gradually increasing and when SOC decreases to 20%, SOC estimation error can reach 9%. Meanwhile, if the battery parameter is updated, the final SOC error is only 2%, which means 7% estimation accuracy improvement can be realized by updating battery parameters using proposed forth-order state estimation method.

![Fig.8 Comparison of SOC estimation result with/without SOH update](image)

**6. CONCLUSION**

This paper proposes a dual time-scale SOC/SOH co-estimation framework for series battery pack with passive balance control. First, by incorporating capacity and resistance into state vector, a fourth-order state equation for the battery cell based on first-order RC ECM is established and particle filter is used to realize state estimation. Then according to definition, the pack’s states boil down to the states of battery cell with minimum capacity and dual time-scale co-estimation framework is proposed considering fast changing property of SOC and slow variation property of SOH. The propose algorithm is verified under battery’s different degradation levels. Results show that capacity estimation error can be beneath 3% if initial guess is 10% deviated from real value. 7% improvement in SOC estimation accuracy can be achieved if battery parameters (including capacity and resistance) are updated by proposed forth-order co-estimation method.

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