Online SOC Estimation Combining EKF and LSTM Algorithm for Reduced Initial SOC Dependency

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ABSTRACT

Extended Kalman filter (EKF) is a promising candidate for online state-of-charge SOC estimation of battery management systems due to its simplicity and fast response. However, the accuracy of the EKF is strongly dependent on the initial SOC status and the impedance model, which degrades the accuracy. On the other hand, the long short-term memory (LSTM) algorithm can estimate the SOC of the battery accurately even in a uncertain initial SOC condition. However, its required computation time is so long that individual SOC estimation for multiple cells is impractical. This paper applies the LSTM algorithm to calibrate the SOC status and impedance model of the battery before EKF estimation is used to detect the SOC status. The proposed algorithm is implemented by Python and is compared with the conventional EKF method. The results show that the proposed method improves the accuracy within RMSE of 0.00667 and reduced the dependency on initial conditions.

Keywords: Extended Kalman filter, Online SOC estimation, State-of-Charge (SOC), Long Short-Term Memory (LSTM).

1. INTRODUCTION

State-of-Charge (SOC) represents the remaining available capacity of the battery, which cannot be measured directly. When estimating SOC in a battery pack consisting of a large number of cells, the characteristic of every cell is assumed to be similar, and then, the SOC of the whole pack is estimated. Unfortunately, the characteristic of the cells becomes mismatching during the aging of the cells, especially in the second-life battery application. Without individual-SOC monitoring for the cells, the conventional operation algorithm can lead the cells to be over-charged or over-discharged due to the battery cell inconsistency. Therefore, The individual-SOC of cells has to be online monitored one by one to ensure the safety of the system [1].

Various methods can be adopted for online SOC estimation. Among those schemes, Extended Kalman Filter (EKF) is a promising method due to its simplicity and fast-response feature [2]-[4]. However, it requires precise initial SOC level and impedance model estimations, which is another big challenge. Besides, the impedance model parameters drift from the original values during the aging of the cells. Thus, EKF requires an enhancement to overcome the disadvantages. On the other hand, the long short-term memory (LSTM) algorithm can estimate the battery SOC accurately even in the unknown initial battery condition [5]-[6]. However, LSTM is known to require a high computation burden that prolongs the processing time.

This paper proposes a coordinated algorithm between EKF and LSTM methods to enhance the accuracy and weaken the dependency on the initial SOC condition. The algorithm is presented in Section 2 and is verified in Section 3. Finally, the conclusion is made in Section 4.

2. PROPOSED METHOD

The conventional EFK method is the most popular method in online SOC estimation due to its simplicity and fast response. The estimation starts from the initial state conditions of the

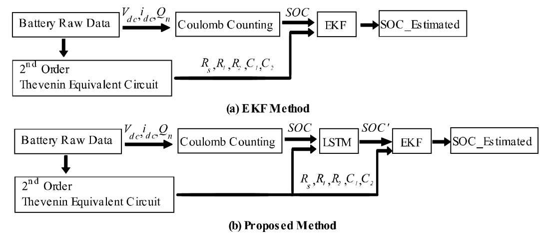

Fig. 1: Concept of the SOC estimation: (a) EKF estimation; (b)Proposed method

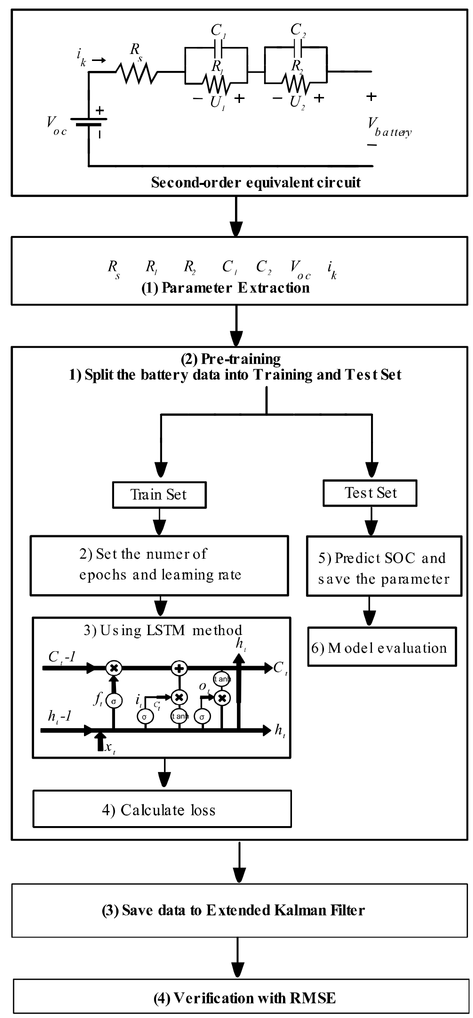

Fig.2: Flowchart of the proposed method

battery, which are predicted based on the equivalent circuit of the battery cell. The second-order Thévenin equivalent model mostly is used to reflect all electrical behaviors of the battery cell. Next, the SOC is estimated by Coulomb counting and is corrected by EKF. Although the calculation time is fast, the estimation accuracy is strongly dependent on correctness of the initial SOC level and the precision of the current sensor. Hence, a relatively large estimation error sometimes occurs.

To mitigate the issue, an LSTM algorithm is inserted between Coulomb counting and EKF estimation stages as Fig. 1. The LSTM is an improved model of Recurrent Neural Network (RNN) Vanishing Gradient Problem so that the hidden unit acts as a gate to control the weight of a self-loop. The Self-loop allows past data to be reflected in current state decisions. And it makes the gradient creates a path that can flow for a long time. In other words, gradients do not disappear.

The parameters of LSTM algorithm are calculated by

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (1)$$

$$f_t = \sigma(W_f [h_{t-1}, x_t] + b_f) \quad (2)$$

$$O_t = \sigma(W_o [h_{t-1}, x_t] + b_o) \quad (3)$$

$$C_t = f_t * C_{t-1} + i_t * C'_t \quad (4)$$

$$C'_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (5)$$

$$h_t = O_t * \tanh(C_t) \quad (6)$$

where i_t is input gate; f_t is forget gate; O_t is output gate; x_t is input; W_i , W_f , W_o , W_c are weight vectors; b_i , b_f , b_o , b_c are biases; C_{t-1} is the memory from the previous LSTM unit; C_t is the memory of new update; C'_t is candidate memory; σ is gate activation function using sigmoid; h_t is the output activation function.

To increase the accuracy, the LSTM is pre-trained by the driven data of the battery in the previous operating cycles. The structure of an LSTM unit is presented in Fig. 2, which is a recurrent type. LSTM is processed by 3 fully-connected gates(input, forget, output) with sigmoid activation function to compute the input gate.

Finally, the SOC is corrected by EKF estimation, based on the procedure in Fig. 2. Compared with the conventional EKF estimation, the proposed method has a higher performance for SOC estimation and can mitigate the uncertain initial battery state data. By applying a pre-training step by LSTM, the proposed method can calibrate the uncertain information either in initial SOC or model paramerters.

3. VERIFICATION TESTS

To verify the performance of the proposed method, 5 charge-discharge cycling process of a cylindrical Li-ion cell (Samsung INR 18650-29E 3.6V/2.9A) is assessed by the battery cycler (Maccor 4300K). Battery is discharged by a constant current of 1C rate and is charged by a CC-CV (4.2V/1C) method. The battery voltage and current are logged for the SOC estimation. Before the test, the proposed method is pre-trained by another driven dataset of the battery cell. The accuracy of the estimation is assessed by the Root Mean Squared Error (RMSE),

$$\text{RMSE} = \sqrt{\frac{\sum(SOC_{estimated} - SOC_{reference})^2}{N}} \quad (7)$$

where $SOC_{estimated}$ is predicted SOC value; $SOC_{reference}$ is reference(actual) SOC value; N is total the number of observation values.

The estimated SOC profiles of the reference and the proposed method are plotted in Fig. 3. The proposed method has a higher performance for estimating SOC than the conventional methods, where the estimated SOC is almost fitted with the reference value. The error profiles of the estimators are illustrated in Fig. 4. Due to the pre-training step, the error becomes very low and RMSE of the proposed method is reduced

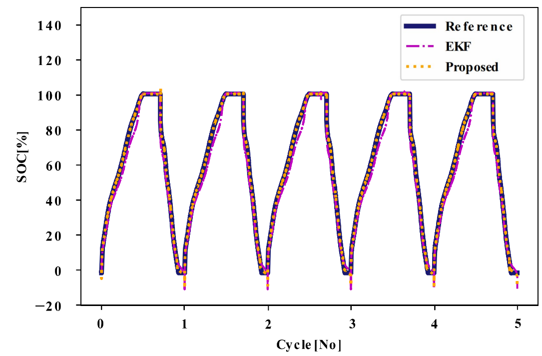

Fig. 3: *Comparison of SOC profiles*

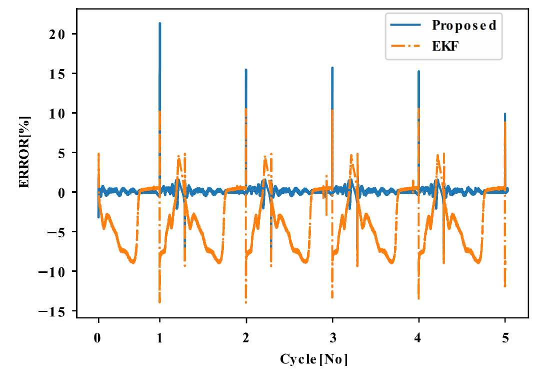

Fig. 4: *Comparison of estimation error.*

to within 0.00667, while the RMSE of the EKF method is 0.04999.

4. CONCLUSION

In this paper, an enhancement of EKF by utilizing the LSTM algorithm is proposed. The SOC is estimated by the LSTM before it is corrected by the EKF estimator. The proposed method is implemented by the TensorFlow and Python Torch deep learning platform. The estimation results show a better accuracy of the proposed method, compared to the conventional EKF.

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