An IoT-based real time inner-state monitoring system for lithium-ion batteries

Takaki Ojima[1,*], Masahiro Fukui[1,†]

[1]*Graduate School of Science and Engineering, Ritsumeikan University*

Abstract

Modern electric vehicles and portable electronic devices necessitate high-performance and reliable battery systems. To achieve this, it is crucial to monitor the battery's state continuously and accurately. In response, there is ongoing development of remote monitoring and history management system for lithium-ion batteries. Against this context, the authors are engaged in the development of a new Battery Management System that integrates real-time battery state estimation capabilities using the Extended Kalman Filter with functions for estimating internal parameters. This paper presents a report on the development of an internal parameter estimation feature for battery state monitoring under various operational conditions, utilizing the Recursive Least Squares method.

Keywords

Lithium-ion battery, Kalman Filter, Recursive Least Square

1. Introduction

Lithium-ion battery (LIB) technology has become essential in many applications, including electric vehicles and portable electronic devices, due to its high energy density and long lifespan. However, LIBs carry the risk of thermal runaway and overcharging, necessitating an advanced Battery Management System (BMS) to ensure safe and efficient use [1, 2]. Furthermore, IoT-based BMSs are becoming increasingly important due to the need for remote monitoring capabilities. The challenge with traditional BMS is that data collection occurs on the battery side (Edge) and data processing occurs in a central system (Host), resulting in delays in reflecting real-time processing results.

Modern BMSs go beyond simple voltage and current monitoring by integrating complex functions such as cell balancing, thermal management, health diagnostics, and predictive maintenance. These functions help to extend battery life and maximize performance. Among these, State of Charge (SOC) estimation is the most important and fundamental technique; SOC is a critical indicator of how much energy remains in the battery. Several SOC estimation methods have been proposed, including the open circuit voltage (OCV) method [3], the Coulomb counting method [4], and the impedance method [5]. However, these methods are affected by

voltage drops due to internal resistance and polarization, making high-precision estimation a challenge. Therefore, several new methods have been proposed to address these shortcomings, such as the Kalman filter method [6, 7], the neural network (NN) method [8], and the sliding mode observer [9]. Among these methods, the Kalman filter is particularly efficient and simple. Kalman filters are suitable for operation on the edge computer side because they can cope with large current fluctuations. Edge computer operation reduces delays in data transmission to the central system and enables real-time battery state estimation. In particular, the Extended Kalman Filter (EKF) provides excellent state estimation for nonlinear systems and accurately captures the battery's real-time behavior, offering robustness against system uncertainties and external noise.

The authors have already incorporated an Extended Kalman Filter (EKF) into the edge computing side for real-time state estimation of batteries. This technology enables the capture of actual battery behavior in real-time, providing robustness against system uncertainties and external noise. However, the accuracy of estimations under specific conditions such as battery degradation and temperature changes may decrease. Therefore, by also integrating the Recursive Least Squares (RLS) method [10], we have enabled real-time updates of internal parameters, achieving high accuracy in state estimation across all operational conditions. This paper reports on the battery remaining capacity estimation functionality that incorporates internal parameter estimation using RLS integrated with EKF.

2. Internal estimation of lithium-ion batteries

This section describes a detailed explanation of Equivalent Circuit Models (ECM), Extended Kalman Filters (EKF), and Recursive Least Squares (RLS). The ECM represents the electrical behavior of batteries through a combination of simple electronic components, helping to understand the dynamic characteristics of batteries. The EKF is used for state estimation of nonlinear systems and accurately tracks the charge state and health of batteries. The RLS method continuously updates the internal parameters of the battery, enabling precise modeling according to changing conditions.

2.1. The Equivalent Circuit Models

The single-stage RC equivalent circuit model commonly used for parameter estimation in storage batteries is shown in Figure 1 [11]. This model can be easily converted into a state-space model and a regression model for parameter estimation. In this model, the battery's electromotive force is represented by a voltage source called Open Circuit Voltage (OCV). The model includes internal resistance, which is divided into two parts: a direct current resistance R_a that represents the charge transfer resistance within the electrolyte, and a parallel circuit consisting of a resistor R_b and a capacitor C_b that represents the slow reaction associated with diffusion. The terminal voltage of the battery is denoted by u_L, and the terminal current is denoted by I. The current flowing into the battery is considered positive. During discharge, I is negative, and during charging, I is positive.
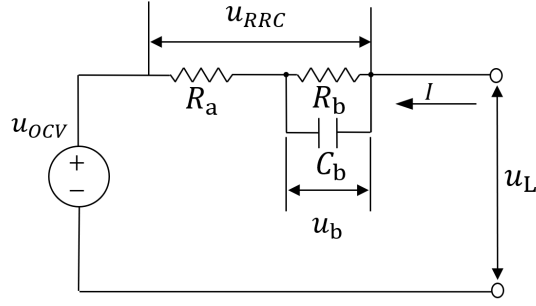
Figure 1: The equivalent circuit model of the Li-ion battery

2.2. Recursive Least Square

To estimate the parameters of a battery online (during charge or discharge mode), the Recursive Least Squares (RLS) method is a conventional identification method. Figure 2 shows the block diagram of parameter estimation with system identification. System identification uses statistical methods to build mathematical models of dynamic systems from measured data. Therefore, the mathematical regression model of the battery must be built from the equivalent circuit model. The differential equation of u_{RRC} (the voltage of R_a and the RC circuit R_b, C_b) is given by equation (1).

$$u_{\text{RRC}} = (R_{\text{a}} + R_{\text{b}})I + R_{\text{a}}R_{\text{b}}C_{\text{b}}\frac{dI}{dt} - R_{\text{b}}C_{\text{b}}\frac{du_{\text{RRC}}}{dt} \tag{1}$$

By using the forward Euler method and the equation $u_{\text{L}} = u_{\text{RRC}} + u_{\text{OCV}}$, equation (2) is derived. T_s is the sampling period.

$$u_{\text{L}}(k) = R_{\text{a}}I(k) + \left(\frac{T_{\text{s}}R_{\text{a}}}{R_{\text{b}}C_{\text{b}}} + \frac{T_{\text{s}}}{C_{\text{b}}} - R_{\text{a}}\right)I(k-1) + \left(\frac{T_{\text{s}}}{R_{\text{b}}C_{\text{b}}} - 1\right)u_{\text{OCV}}(k)$$
$$- \left(\frac{T_{\text{s}}}{R_{\text{b}}C_{\text{b}}} - 1\right)u_{\text{L}}(k-1) + u_{\text{OCV}}(k) \tag{2}$$

Through the variable transformation shown in equation (3), the regression model of the battery can be written as equation (4).

$$a_1 = \frac{T_{\text{s}}}{R_{\text{b}}C_{\text{b}}}, \quad f = (1 + a_1)u_{\text{OCV}}$$
$$b_0 = R_{\text{a}}, \quad b_1 = \frac{T_{\text{s}}R_{\text{a}}}{R_{\text{b}}C_{\text{b}}} + \frac{T_{\text{s}}}{C_{\text{b}}} - R_{\text{a}} \tag{3}$$
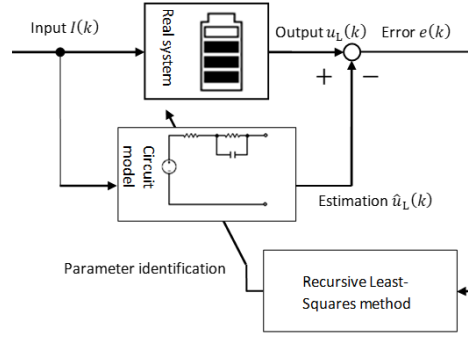
Figure 2: Block diagram of internal parameters estimation

$$y(k) = u_{\mathrm{L}}(k) = \varphi^{\mathrm{T}}(k)\theta$$

$$\varphi(k) = \begin{bmatrix} i(k) \\ i(k-1) \\ -u_L(k-1) \\ 1 \end{bmatrix}, \quad \theta = \begin{bmatrix} b_0 \\ b_1 \\ a_1 \\ f \end{bmatrix} \tag{4}$$

In equation (4), is considered an unknown parameter to be estimated using RLS identification. The values of R_a, R_b, C_b, and u_{OCV} can be calculated from the parameter θ using equation (5).

$$R_a = b_0, \quad R_b = \frac{b_1 - a_1 b_0}{1 + a_1}$$

$$C_b = \frac{T_s}{b_1 - a_1 b_0}, \quad u_{OCV} = \frac{f}{1 + a_1} \tag{5}$$

Following the RLS identification theory, the evaluation function with a forgetting factor for the RLS is given by equation (6). λ is forgetting factor, a positive number less than 1.

$$J(k) = \sum_{i=1}^{k} \lambda^{k-i} e^2(i) \tag{6}$$

The RLS algorithm to minimize the equation (6) is described as Algorithm 1. $\theta(k)$ is the estimated value of the parameters at time k, $\boldsymbol{P}(k)$ is error-covariance matrix at time k, $\boldsymbol{I}$ is identity matrix, $\hat{\theta}(0)$ is the initial value of the parameter setting, $\boldsymbol{P}(0)$ is the initial error-covariance matrix setting.

2.3. Extended Kalman Filters

In recent studies, the method for estimating SOC based on the extended Kalman filtering (EKF) technique has been proposed. The EKF is an approximately optimal state estimator for a

Algorithm 1 RLS

Initialization Value:
$\widehat{\theta}(0) = \theta_0$
$\boldsymbol{P}(0) = \gamma \boldsymbol{I}$ γ is a positive number
$0 \ll \lambda < 1$ Forgetting factor

Recursive Process:
$e(k) = y(k) - \boldsymbol{\varphi}^{\mathsf{T}}(k)\widehat{\boldsymbol{\theta}}(k-1)$

$$\boldsymbol{P}(k) = \frac{1}{\lambda}\left\{ \boldsymbol{P}(k-1) - \frac{\boldsymbol{P}(k-1)\boldsymbol{\varphi}(k)\boldsymbol{\varphi}^{\mathsf{T}}(k)\boldsymbol{P}(k-1)}{\lambda + \boldsymbol{\varphi}^{\mathsf{T}}(k)\boldsymbol{P}(k-1)\boldsymbol{\varphi}(k)} \right\}$$

$$\widehat{\boldsymbol{\theta}}(k) = \widehat{\boldsymbol{\theta}}(k-1) + \frac{\boldsymbol{P}(k-1)\boldsymbol{\varphi}(k)}{\lambda + \boldsymbol{\varphi}^{\mathsf{T}}(k)\boldsymbol{P}(k-1)\boldsymbol{\varphi}(k)}e(k)$$

Table 1
The Details of State Space Model

$A(k) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1-\frac{T_s}{R_bC_b} & 0 \\ 0 & 0 & 1 \end{bmatrix}$		$B(k) = \begin{bmatrix} \frac{T_s}{FCC} \\ \frac{T_s}{C_b} \\ 0 \end{bmatrix}$
$h(x(k)) = u_{OCV} + u_b + IR_a$		
State Vector		$x(k) = \begin{bmatrix} SOC(k) \\ u_b \\ R_a \end{bmatrix}$
Control Input		$u(k) = I(k)$
Observation Value		$y(k) = u_L(k)$

nonlinear stochastic process subject to Gaussian white noises using state-space model.

$$x(k+1) = A(k)x(k) + B(k)u(k) + w(k) \tag{7}$$

$$y(k) = C(k)x(k) + v(k) \tag{8}$$

Where equations (7) and (8) are the state and observation equations, respectively; $x(k)$, $y(k)$ and $u(k)$ are the state vector, observed output, and control input, respectively. The signal $w(k)$ is the process noise, and $v(k)$ is the observation noise. We assume that these noises are zero-mean white Gaussian noise processes with covariance σ_w^2 and σ_v^2 respectively. For battery equivalent circuit model, the detail of state space model is shown in Table 1.

The EKF algorithm is described as Algorithm 2. This algorithm consists of three steps: Initialization, Prediction, and Filtering. Here, $\hat{x}^-$ is the one-step prediction vector, $\hat{x}$ is the filtered estimate vector, P^- is the prediction error covariance matrix, and P is the filtering error covariance matrix. In this paper, P is different from $\boldsymbol{P}$. $\boldsymbol{P}$ is the error covariance matrix of RLS, P is the covariance matrix of EKF. As represented in equation (9), $C(k)$ is the Jacobian matrix of $h(x(k))$, which represents the nonlinear relationship between OCV and SOC.
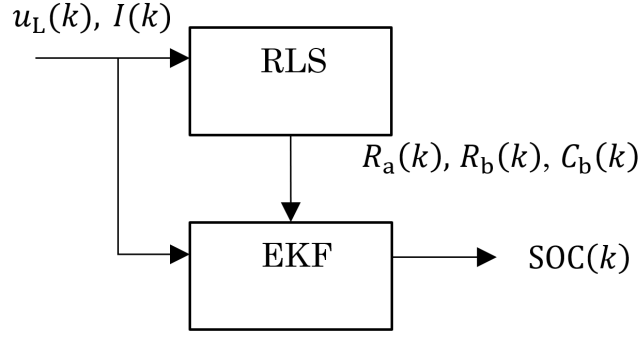
Figure 3: The block diagram of the parameter and state estimation

$$C(k) = \left. \frac{\partial h(x(k))}{\partial x(k)} \right|_{x(k)=\widehat{x(k)}} = \left[\left. \frac{dOCV}{dSOC} \right|_{SOC=\widehat{SOC}}, 1, I(k) \right] \tag{9}$$

Algorithm 2   EKF

Initialization Value:
$\widehat{\chi}_0^-, P_0^-$

Filtering Step:
$g_{k+1} = P_{k+1}^- C^T / (C P_{k+1}^- C^T + \sigma_v^2)$
$\hat{x}_{k+1} = \hat{x}_{k+1}^- + g_{k+1}(y_{k+1} - \hat{y}_{k+1}^-)$
$P_{k+1} = (1 + g_{k+1}C)P_{k+1}^-$

Prediction Step:
$\hat{x}_{k+1}^- = A\hat{x}_k + Bu_k$
$P_{k+1}^- = AP_k A^T + \sigma_w^2$

2.4. The parameter and state estimation

Figure 3 shows the block diagram of the series parameter and state estimation. In this block diagram, the RLS block performs parameter estimation, and the EKF (Extended Kalman Filter) block performs state estimation. The RLS must simultaneously estimate the OCV and the parameters of the RC circuit ($R_a(k)$, $R_b(k)$, $C_b(k)$). Therefore, it is difficult to guarantee the accuracy of the OCV and RC circuit estimations, which in turn affects the accuracy of the SOC estimation.
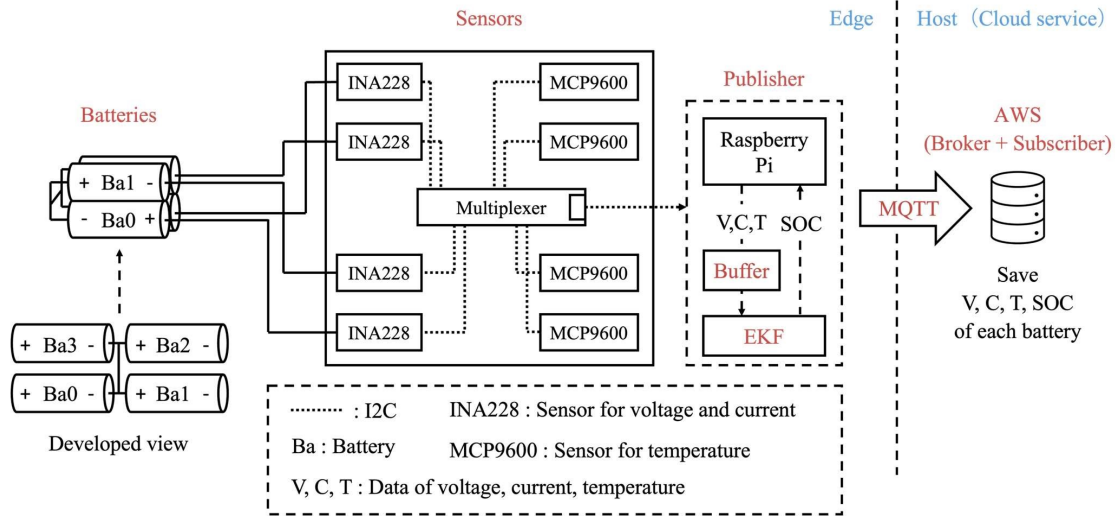
Figure 4: The BMS architecture

3. The IoT-based Battery Management System

3.1. The BMS Architecture

Figure 4 shows the BMS architecture. The BMS consists of six components: First, a battery pack composed of four lithium-ion batteries (Batteries). Second, sensors that measure voltage, current, and temperature from each lithium-ion battery (Sensors). Third, a temporary storage for the data measured by the sensors (Buffer). Fourth, an Extended Kalman Filter (EKF) used to estimate SOC (State of Charge) based on the measured data. Fifth, a Publisher that sends voltage, current, temperature, and SOC data to AWS (Amazon Web Services). Sixth, AWS which stores and manages all the data.

3.2. State estimation module with RLS

Figure 5 shows the State estimation module with RLS. Based on the architecture shown in Figure 4, RLS was introduced, and a battery internal parameter estimation function was added. The changes were made by the publisher on the edge computer side. Previously, the SOC was estimated by fixing the battery's internal parameters at their default values. This time, it has been changed so that the battery's internal parameters are estimated in real-time by RLS and used for SOC estimation.

4. The Test Experiments and Results

In this paper, we have added a battery internal parameter estimation function using RLS to a BMS with SOC estimation capabilities based on EKF. To verify its proper functioning, we examined SOC estimation using EKF with and without RLS. The estimation experiments utilized discharge
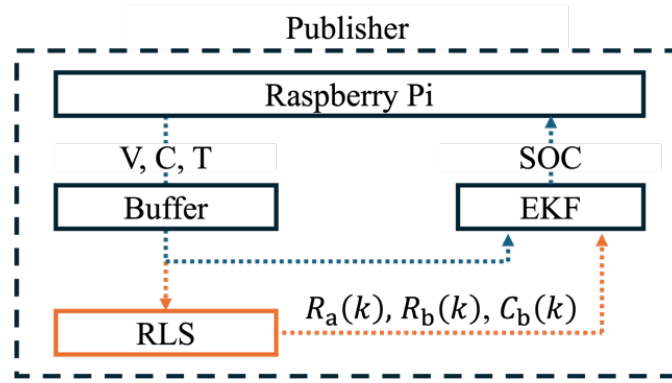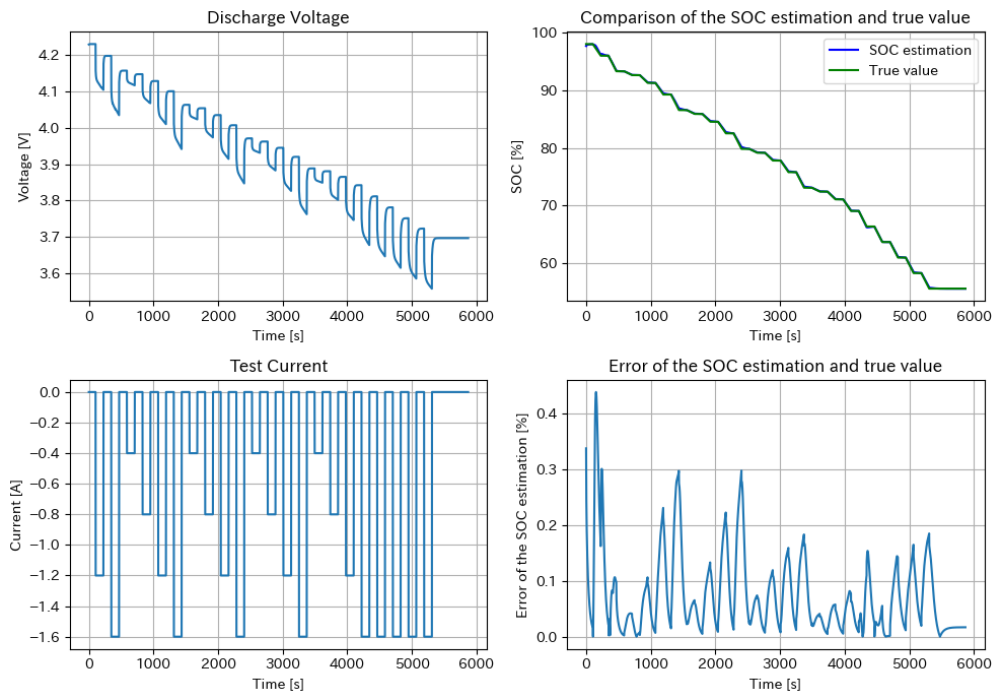
Figure 5: State estimation module with RLS

Figure 6: The SOC estimation result by EKF-RLS

waveforms of 18650-type lithium-ion batteries. Various patterns of discharge waveforms were prepared, and the measured terminal voltage and current were input into the RLS-EKF algorithm to simultaneously estimate circuit parameters and SOC. Figure 6 shows the terminal voltage, terminal current, our SOC estimation results, the true SOC values, and their absolute errors. Additionally, Figure 7 shows the estimation results of the internal parameters using RLS. Figure 8 shows the Comparison of SOC Estimation Results Using EKF with and without RLS. By adding RLS, it is confirmed that SOC can be estimated with higher accuracy.
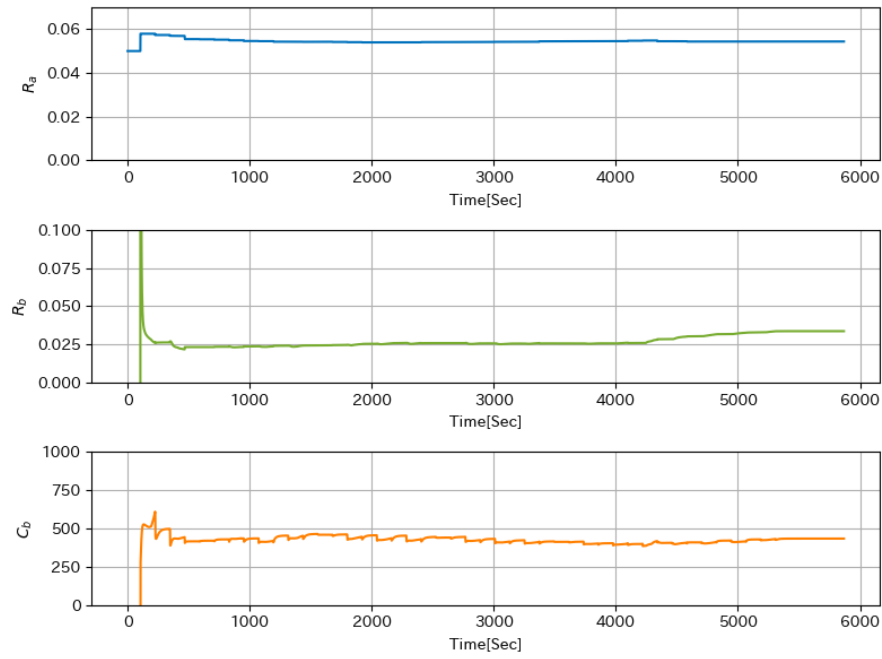
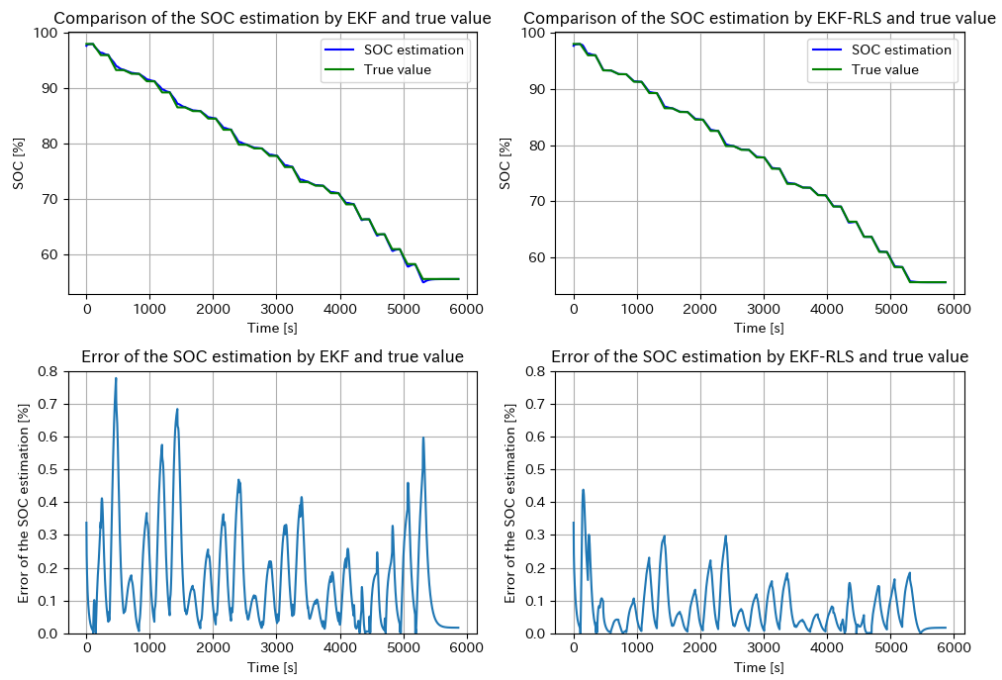**Figure 7:** The inner parameter estimation of Lithium-ion battery

Figure 8: The Comparison of SOC Estimation Results Using EKF with and without RLS

5. Conclusion

In this study, a function for estimating internal parameters by RLS was added to a real-time battery condition monitoring system. This function is expected to enable more accurate estimation of the state of the battery, which depends on the state of degradation and temperature changes. At the present stage, the functionality of the BMS has not been evaluated in a real environment, so the accuracy of the SOC estimation and the influence of the internal parameter estimation will be evaluated in a real environment in the future.

Acknowledgments

References

[1] P. Weicker, A systems approach to lithium-ion battery management, Artech house, 2013.

[2] K. Liu, K. Li, Q. Peng, C. Zhang, A brief review on key technologies in the battery management system of electric vehicles, Frontiers of mechanical engineering 14 (2019) 47–64.

[3] K.-S. Ng, C.-S. Moo, Y.-P. Chen, Y.-C. Hsieh, State-of-charge estimation for lead-acid batteries based on dynamic open-circuit voltage, in: 2008 IEEE 2nd International Power and Energy Conference, IEEE, 2008, pp. 972–976.

[4] K. S. Ng, C.-S. Moo, Y.-P. Chen, Y.-C. Hsieh, Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries, Applied energy 86 (2009) 1506–1511.

[5] S. Rodrigues, N. Munichandraiah, A. Shukla, A review of state-of-charge indication of batteries by means of ac impedance measurements, Journal of power Sources 87 (2000) 12–20.

[6] G. L. Plett, Extended kalman filtering for battery management systems of lipb-based hev battery packs: Part 2. modeling and identification, Journal of Power sources 134 (2004) 262–276.

[7] G. L. Plett, Extended kalman filtering for battery management systems of lipb-based hev battery packs: Part 3. state and parameter estimation, Journal of Power sources 134 (2004) 277–292.

[8] W. He, N. Williard, C. Chen, M. Pecht, State of charge estimation for li-ion batteries using neural network modeling and unscented kalman filter-based error cancellation, International Journal of Electrical Power & Energy Systems 62 (2014) 783–791.

[9] T. Kim, W. Qiao, L. Qu, Online soc and soh estimation for multicell lithium-ion batteries based on an adaptive hybrid battery model and sliding-mode observer, in: 2013 IEEE energy conversion congress and exposition, IEEE, 2013, pp. 292–298.

[10] C. Fleischer, W. Waag, H.-M. Heyn, D. U. Sauer, On-line adaptive battery impedance parameter and state estimation considering physical principles in reduced order equivalent

circuit battery models part 2. parameter and state estimation, Journal of Power Sources 262 (2014) 457–482.

[11] M. S. Grewal, A. P. Andrews, Kalman filtering: Theory and Practice with MATLAB, John Wiley & Sons, 2014.