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State of Charge Estimation of Li-ion Batteries Considering Uncertainties Due to Sensor Measurement Biases and Temperature Variations

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Abstract – **Different uncertainties such as the sensor measurement errors and varying operating temperatures cause an error in battery model parameters, which, in turn, adversely affects the accuracy of the state of charge (SoC) estimation algorithm used in the battery management system. This paper proposes an SoC estimation method of the Li-ion battery that adopts a temperature-compensated battery model to deal with the varying model parameters that change with operating temperatures and a dual extended Kalman filter (DEKF) to estimate the SoC considering sensor measurement errors/biases. This study only focuses on the voltage and current sensor measurement error estimation in the DEKF framework, together with SoC estimation. The performance of the DEKF with biases elimination is compared with the DEKF without the elimination of biases. The efficacy of the proposed method is validated through extensive experimental investigation, and the results show that the SoC of the Li-ion battery can be estimated effectively with higher accuracy.**

Index Terms—**Energy storage; Li-ion battery; temperature compensated model estimation; sensor measurement errors; state of charge.**

I. Introduction

Battery energy storage (BES) is one of the most critical elements in the fast thriving renewable energy (RE) based micro-grid, smart grid, and electric vehicular (EV) applications where the BES facilitates higher flexibility, efficiency, affordable cost of energy, and reduced carbon emissions to the environment [1]. An accurate state of charge (SoC) estimation of the BES is one of the most critical and challenging tasks. It is both critical and challenging because different uncertainties play a vital role in an erroneous SoC estimation [2, 3]. The most common uncertainties that result in an erroneous SoC estimation are sensor measurement errors/biases, operating conditions uncertainties such as operating temperatures and loading conditions, algorithm uncertainties, battery modeling, and parameter uncertainties [2]. In recent years, different approaches, for example, family of Kalman filters [3-5], maximum-likelihood method (MLM) [6, 7], polynomial regression method [2], and Gaussian process (GP) regression method [2, 7, 8], etc. are explored for both uncertainties modeling and reliable SoC estimation of the battery.

In [2], the model uncertainties of the Li-ion battery is modeled with both polynomial and Gaussian process (GP) regression method. Further, those polynomial and GP regression models are augmented with traditional extended Kalman filter (EKF) for improved SoC estimation. It is observed that the GP-EKF outperformed the polynomial regression-EKF method because of the superior dealing capability of the GP regression method with highly nonlinear and complex nature of the model bias concerning various battery operation conditions. However, other significant uncertainties, such as sensor measurement biases and operational uncertainties such as temperature effects, were not studied in this paper. In [4], the bias/error in SoC estimation caused by voltage and current sensors are theoretically and systematically analyzed. The authors used both the Kalman filter and the least-squares method for SoC estimation under sensor bias and variances. This study reported that the overall SoC estimation error ranges between 0-5.3 percent, where the sensor noises contributed to up to 0-3 percent of SoC estimation error and the rest caused by the model uncertainty. However, the author did not consider the SoC estimation error from the variation of operating temperatures, which is believed to be the most common source of uncertainties that the SoC estimation methods suffer [9, 10].

A mitigation technique of the effects of process and measurement uncertainty in the SoC estimation is presented in [6], where the author used the conventional EKF and maximum-likelihood approach. Although the performance of traditional EKF enhanced with the proposed method, the author assumed the model parameters are constant over time, but changes in the model parameters are inevitable due to a change in operating conditions [10-12]. In [13], a dual extended Kalman filter (DEKF) and augmented EKF are developed for the estimation of both SoC and state of health (SoH) of Li-ion batteries. The author included the temperature effects in the study but used constant values of the sensor measurement and process errors. However, the authors in [13] did not consider the cell fast and slow hysteresis components as the model parameters (R and C parameters), which were found to be the critical SoC affecting parameters in recent studies. The suitability of a DEKF is explored in [3] for SoC, SoH, and model parameters evaluation of Li-ion batteries. Similar to [13], the authors in this paper avoided the hysteresis model parameters and other SoC affecting uncertainties. Both model and parameter uncertainties are investigated in [7], where the authors applied MLM for parameter uncertainty modeling and GP regression for model uncertainty modeling of the Li-ion battery. After quantification of those uncertainties, this study used EKF for both SoC and SoH estimation. The corrected battery model used in this study was able to enhance SoC estimation, but transient resistance and capacitances were not considered as model parameters, and all the tests were performed at a constant temperature. In [8], GP regression was used for the SoC estimation of Li-ion batteries. The input data for training the GP model were voltage, current, and temperature, whereas the output was SoC. However, this study mainly determined the performance of different kernel functions of GP for reliable SoC estimation.

It is reported in [2, 4] that the sensor measurement errors, for instance, voltage and current measurement errors and operating condition uncertainties due to the variation of operating temperatures, are the primary source of SoC estimation error. With the view of the above literature review, it can be summarized that the effects of sensor measurement uncertainties such as voltage and current measurement errors and operating condition uncertainties due to the variation of operating temperatures did not get enough attention yet. Recently, although some studies [4, 6] tried to address the sensor measurement uncertainties in reliable SoC estimation, the authors did not consider the environmental uncertainties arises from variable operating temperatures. As a result, this study aims to contribute to the following aspects:

- Temperature-compensated online model parameters identification of the Li-ion battery based on a time-varying battery model.
- Online estimation of sensors measurement errors and SoC of the Li-ion battery based on dual extended Kalman filter (DEKF).

II. PROPOSED BATTERY MODELING AND SOC ESTIMATION TECHNIQUE

An accurate battery model that can capture a real battery cell's dynamics is required for a reliable and correct SoC estimation. The most commonly used battery models in the SoC estimation domain are equivalent circuit based battery models [1, 14], electrochemical battery models [15-17], and machine learning-based battery models [18-20]. A Thevenin based equivalent circuit model (ECM) of Li-ion battery with two RC circuits and possible uncertainties is presented in Fig.1 where, $V_{ocv}\{SoC, \alpha(p)\}$, $V_{st}\{SoC, \alpha(p)\}$ and $V_{st}\{SoC, \alpha(p)\}$ are the open-circuit voltage (OCV), short-time and long-time transient voltage of the battery cell under no-load condition, respectively. These voltage components are the function of SoC and possible uncertainties such as operating temperature, charge/discharge current, capacity, etc. In Fig.1, $\alpha(p)$ is the possible environmental uncertainties such as operating temperature and loading conditions. This paper considered the operating temperature as the only environmental uncertainties/biases. Here V_b is the measured battery terminal voltage, whereas, I_b is the measured charging or discharging current of the battery cell. This voltage and current are measured by sensors that may possess biases/errors in the measurement.

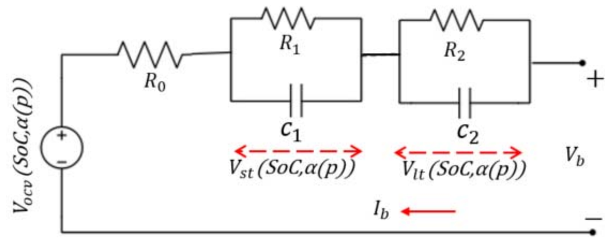

Fig. 1: An equivalent circuit model of Li-ion batteries with possible uncertainties.

Considering the sensor bias in the voltage and current measurement as V_b^{Θ} and I_b^{Θ}, respectively, the actual voltage and current equation from Fig.1 can be written as follows

$$V = V_b - V_b^{\Theta}; I = I_b - I_b^{\Theta} \tag{1}$$

Both sensor and environmental uncertainty under consideration, the actual continuous time-domain terminal voltage of the cell, can be written as follows

$$V = V_{ocv}(SoC,T) - R_0 I - V_{st}(t) - V_{lt}(t) \tag{2}$$

Using the standard technique such as KCL and KVL, the transient voltage components in (2) can be obtained as follows

$$V_{st}(t) = V_{st,1}\left(1 - e^{-t/R_1 C_1}\right); V_{lt}(t) = V_{lt,2}\left(1 - e^{-t/R_2 C_2}\right) \tag{3}$$

As reported in [14], the offline model parameters (non-time varying) at fixed operating temperatures can be extracted by applying system identification and final value theorem [1, 14]:

$$\left.\begin{aligned} & V_0 = IR_0; R_p(SoC) = \frac{V_{st,ss}}{I} = \frac{V_{lt,ss}}{I} \\ & C_p(SoC) = \frac{\tau_1}{R_1} = \frac{\tau_2}{R_2} \end{aligned}\right\}, p = 1,2 \tag{4}$$

In (4), V_0 is the ohmic voltage drop caused by R_0, $V_{st,ss}$ and $V_{lt,ss}$ are fast and slow transient voltages at steady-state conditions caused by first and second RC circuits, respectively. This study has been extracted those offline model parameters at some fixed operating temperatures using (4), followed by performing a few pulse discharge tests of the battery cell in the laboratory. The details of these pulse discharge tests will be discussed in III. The relationship between model parameters $(R_0 - SoC, R_p - SoC, C_p - SoC)$ and SoC at a particular operating temperature can be described as shown in Fig.2.

In Fig.2, the model parameters are the functions of SoC only. However, in practice, those model parameters change over time as the SoC level, and operating temperature (T) changes. As a result, it is essential to extract those model parameters online as a function of SoC and operating temperatures. As presented in Fig.2, it can be seen that the ohmic resistance does not have significant changes over the entire SoC ranges and with the changes of operating temperatures whereas, the model parameters of the RC parallel branches have a nonlinear relationship and changes significantly with the SoC and operating temperatures changes.

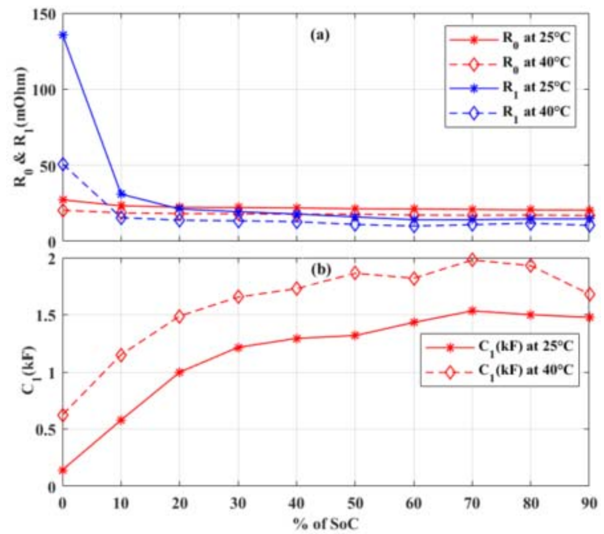

Fig. 2: Offline model parameters of Li-ion battery vs. SoC at 25°C and 40°C temperatures.

By training different polynomial regression model in Matlab with the offline model parameters and SoC, it is found that the transient resistances and capacitances are balanced fit with the polynomial regression model presented in (5):

$$\left.\begin{aligned} R_p &= a_1 + b_1\, e^{-c_1 SoC} \\ C_p &= d_1 + e_1\, e^{-f_1 SoC} \end{aligned}\right\}, p = 1,2. \quad (5)$$

Upon collecting the coefficients $a_{1,2}$, $b_{1,2}$, $c_{1,2}$, $d_{1,2}$, $e_{1,2}$, and $f_{1,2}$ at different fixed operating temperatures, one can estimate temperature-dependent co-efficient $a_{1,2}(T)$, $b_{1,2}(T)$, $c_{1,2}(T)$, $d_{1,2}(T)$, $e_{1,2}(T)$ and $f_{1,2}(T)$. A generic formula to compute that temperature-dependent coefficient is demonstrated as follows

$$a_1\left(T\right) = A_1 + B_1\, e^{-C_1 T^1} \quad (6)$$

Upon extracting $a_{1,2}(T)$, $b_{1,2}(T)$, $c_{1,2}(T)$, $d_{1,2}(T)$, $e_{1,2}(T)$ and $f_{1,2}(T)$ one can extract both SoC and temperature-dependent online model parameters as follows

$$\left.\begin{aligned} R_p\left(SoC,T\right) &= a_1\left(T\right) + b_1\left(T\right) e^{-c_1\left(T\right) SoC} \\ C_p\left(SoC,T\right) &= \sum_{j=1}^{2} d_j\left(T\right) SoC^j + e_3\left(T\right) \end{aligned}\right\}, p = 1,2. \quad (7)$$

After extracting the model parameters as a function of both SoC and operating temperature (environmental uncertainty), the augmented discrete domain state-space battery equations can be written as of (8-9), where SoC, transient voltage components, voltage, and current sensor bias are the states of the battery cell.

$$V_{b,k} = V_{ocv}(SOC_{k-1}, T_{k-1}) - V_{st,k-1} - V_{lt,k-1} - IR_s + V^{\Theta}_{b,k-1} \quad (8)$$

$$\begin{bmatrix} SOC_k \\ V_{st,k} \\ V_{lt,k} \\ I^{\Theta}_{b,k} \\ V^{\Theta}_{b,k} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & {dt}/{C_N} & 0 \\ 0 & e^{-dt/\tau_1(SoC,T)} & 0 & -R_1(SoC,T)\left(1-e^{-dt/\tau_1(SoC,T)}\right) & 0 \\ 0 & 0 & e^{-dt/\tau_1(SoC,T)} & -R_2(SoC,T)\left(1-e^{-dt/\tau_2(SoC,T)}\right) & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} SOC_{k-1} \\ V_{st,k-1} \\ V_{lt,k-1} \\ I^{\Theta}_{b,k-1} \\ V^{\Theta}_{b,k-1} \end{bmatrix} + \begin{bmatrix} -dt/C_N \\ R_1(SoC,T)\left(1-e^{dt/\tau_1(SoC,T)}\right) \\ R_2(SoC,T)\left(1-e^{dt/\tau_2(SoC,T)}\right) \\ 0 \\ 0 \end{bmatrix} I \quad (9)$$

Equation (8) and (9) are the nonlinear measurement and state transition function of the Li-ion battery, respectively.

After formulating the augmented matrices in (8-9), this paper adopts a dual extended Kalman filter (DEKF) for the simultaneous estimation of SoC and sensor biases. Fig.3 shows the schematic process diagram of a DEKF where the 1st filter estimates the fast-varying states (SoC and transient voltage components), and the 2nd filter synchronously determines the slow-varying parameters (sensor biases) of the plant model within the 1st filter.

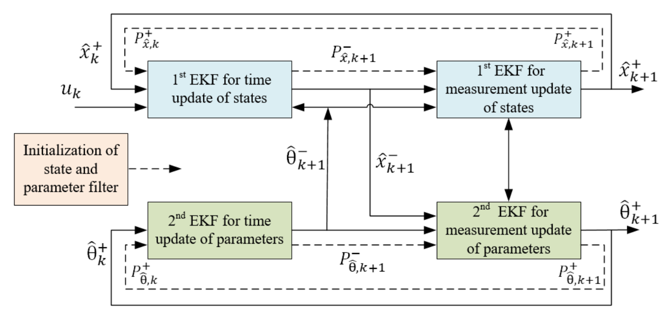

Fig. 3: DEKF schematic process map.

In Fig.3, the state filter (1st EKF) runs with priority so that the remaining voltage error can be used by the parameter or weight filter (2nd EKF) to adjust the parameters accordingly. At each operating point, both filters exchange information about the estimation recursively. To be used in the DEKF, the nonlinear state transition and measurement function of the Li-ion battery presented in (8-9) can be written as follows

$$\left.\begin{aligned} x_{k+1} &= f\left(x_k, u_k, \theta_k\right) + \Sigma_d; \quad \Sigma_d = N(0, D^x_k) \\ y_k &= g\left(x_k, u_k, \theta_k\right) + \Sigma_s; \quad \Sigma_s = N\left(0, S^x_k\right) \end{aligned}\right\} \quad (10)$$

In (10), $f(x_k, u_k, \theta_k)$ and $g(x_k, u_k, \theta_k)$ are nonlinear state transition and measurement function respectively whereas, $\sum_d$ and $\sum_s$ are covariance matrices of process noise (D_k^x) and measurement noise (S_k^x) respectively. The dynamics for the 2nd weight/parameter filter that estimates the parameters can be defined as

$$
\left.\begin{aligned}
\theta_{k+1} &= \theta_k + \textstyle\sum_r; & \textstyle\sum_r &= N\left(0, D_k^{\theta}\right) \\
z_k &= g\left(x_k, u_k, \theta_k\right) + \textstyle\sum_e; & \textstyle\sum_e &= N\left(0, S_k^{\theta}\right)
\end{aligned}\right\} \tag{11}
$$

In (11), $\sum_r$ and $\sum_e$ are the covariance matrices of parameter process noise (D_k^{θ}) and measurement noise (S_k^{θ}), respectively. The parameters that need to be estimated adaptively in (11) can be presented as follows

$$\theta_k = \left[V_b^{\Theta}, I_b^{\Theta}\right]^T \tag{12}$$

With the battery state dynamics and parameter dynamics defined, the DEKF adopted in this study is presented in Fig.4. In Fig.4, the definitions of F_{k-1}, G_k^x and G_k^{θ} are as follows,

$$
F_{k-1} = \left.\frac{\partial f\left(x_{k-1}, u_{k-1}, \hat{\theta}_k^-\right)}{\partial x_{k-1}}\right|_{x_{k-1}=\hat{x}_{k-1}^+} ; G_k^x = \left.\frac{\partial g\left(x_{k-1}, u_{k-1}, \hat{\theta}_k^-\right)}{\partial x_k}\right|_{x_k=\hat{x}_k^+}
$$

$$
G_k^{\theta} = \left.\frac{dg\left(x_{k-1}, u_{k-1}, \theta\right)}{d\theta}\right|_{\theta=\hat{\theta}_k^-} \tag{13}
$$

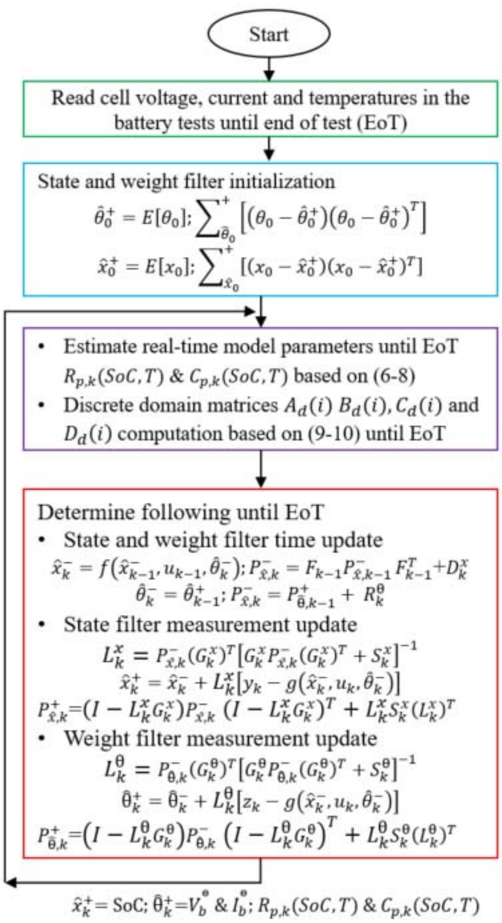

Fig. 4: Flowchart of the proposed temperature compensated battery model and DEKF frameworks.

III. EXPERIMENTAL SETUP

An experimental setup has been built in the laboratory to carry out pulse discharge (PD) tests. This study develops a program in the LabVIEW platform to control the PD test, and the proposed temperature-compensated battery model and dual extended Kalman filter (DEKF) have been incorporated in the LabVIEW program for the SoC and sensor measurement errors estimation of the Li-ion battery. Table 1 lists and describes the components used in the test.

Table 1: Experimental setup description

Components	Ratings and roles in the tests.
Battery cell	• $LiFePO_4$ cells (IFR26650) • Nominal capacity 3.3Ah at 0.2C • Nominal voltage 3.2V • Operating temperatures -20ºC to 60ºC • Discharge cut-off at 2V.
Programmable DC power supply	• Charging the cell in CCCV method developed in LabVIEW
Programmable DC load	• Electro-Automatik (EL 9000) 2.4kW load
PT100 sensors	• Ambient and cell temperatures measurement
National instrument (LabVIEW) devices	• NI 9229 voltage and current measurement and data acquisition. • NI 9217 cell and ambient temperatures data acquisition.
High-speed computer	• Data recording and LabVIEW program development.

IV. RESULT AND DISCUSSION

A temperature-compensated battery model is developed for online model parameters estimation, whereas a dual extended Kalman filter (DEKF) is developed for real-time estimation of sensor measurement biases and SoC of a Li-ion battery cell. The proposed temperature-compensated battery model and DEKF have been implemented in the LabVIEW platform to perform pulse discharge experiments on Li-ion battery cells. Fig.5 illustrates (a) the operating temperatures variation, (b) the current and voltage in pulse discharge (PD) test, (c) voltage and current sensor measurement error, and (d) SoC estimated by DEKF with and without biases elimination. As presented in Fig.5 (a), the operating temperature starts with 26.61°C, and it increases during the 368sec PD periods. After a short PD of 368sec, a 1hour rest period starts. In the first half of the rest period of the cell, the operating temperature stabilized, and a new temperature was set for the rest next 1800sec. After this, the 2nd PD starts with this temperature set point. This temperature variation procedure continues in the entire SoC level of the discharge test. The considered temperature range is between 29.1°C to 33°C.

As presented in Fig.5 (b), the battery cell is pulse discharged at 1C discharge rate (3.434A) until the cell cut-off voltage reaches 2V. In each of the pulse discharge period, a 10% SoC depletion goal has been set in the LabVIEW program. It is observed from Fig.5 (b) that the cell voltage suffers a quick fall when the SoC level of the cell is between 10% to 0%. %. As presented in Fig.5 (c), the real-time voltage and current sensor measurement biases are estimated in the DEKF method. Both voltage and current sensor biases are oscillated before setting to a stable value. The current sensor bias is found to be 49-55mA, which is 1.43-1.61% of the maximum cell current measured in this study. On the other hand, voltage sensor bias is found to be 52mV, which is 1.46% of the maximum cell voltage measured. Fig.5 (d) presents the comparison of SoC estimated by the adopted DEKF with and without bias elimination. It is found that the adopted DEKF has the ABE ranges between 0-3percent in the SoC level of 100-20%. Again, the ABE ranges between 5-10% in the rest of the SoC level for the adopted DEKF with the sensor measurement error elimination. On the other hand, the adopted DEKF method without biases elimination suffers much higher ABE in the cell's entire discharge period. For instance, the ABE reaches 10-25% when the SoC level is between 20-0%.

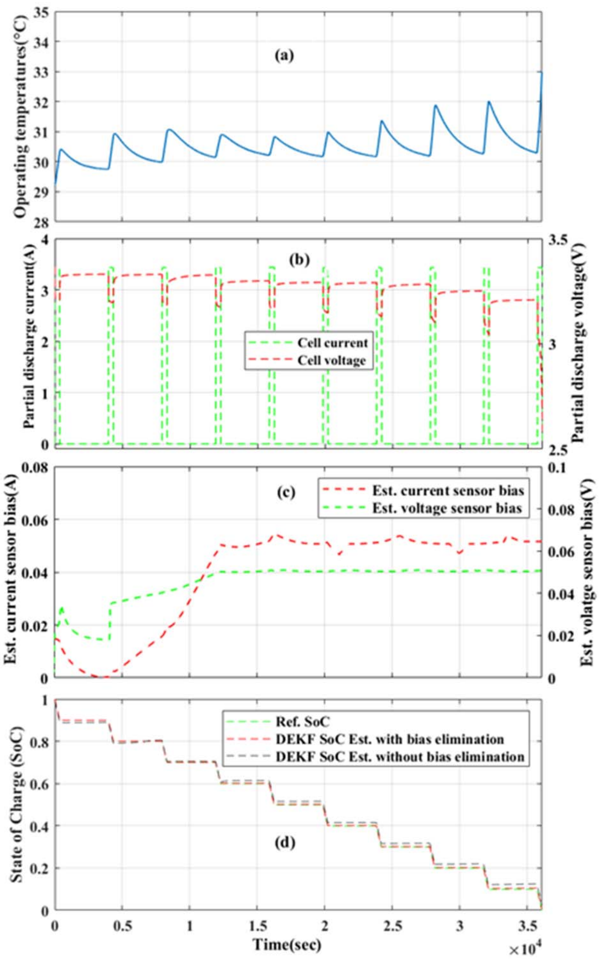

Fig. 5: voltage, current sensor measurement errors/biases, and SoC estimated in the PD test of Li-ion battery with the proposed method.

Fig.6 (a) and (b) present the real-time short transient resistance and capacitance, respectively, whereas Fig.6 (c) and (d) illustrate the real-time long transient resistance and capacitance, respectively, in the PD test. It can be observed that the short and long transient capacitances show highly varying characteristics during the entire pulse discharge (PD) test of the cell. As the level of SoC of the cell depletes, the values of short and long transient resistance increases. On the other hand, the values of short and long transient capacitance decrease as the level of SoC depletes. After analyzing and finding this study, we can claim that the proposed temperature compensated dual extended Kalman filter (DEKF) method shows higher accuracy and effectiveness in the SoC and sensor biases estimation of Li-ion battery.

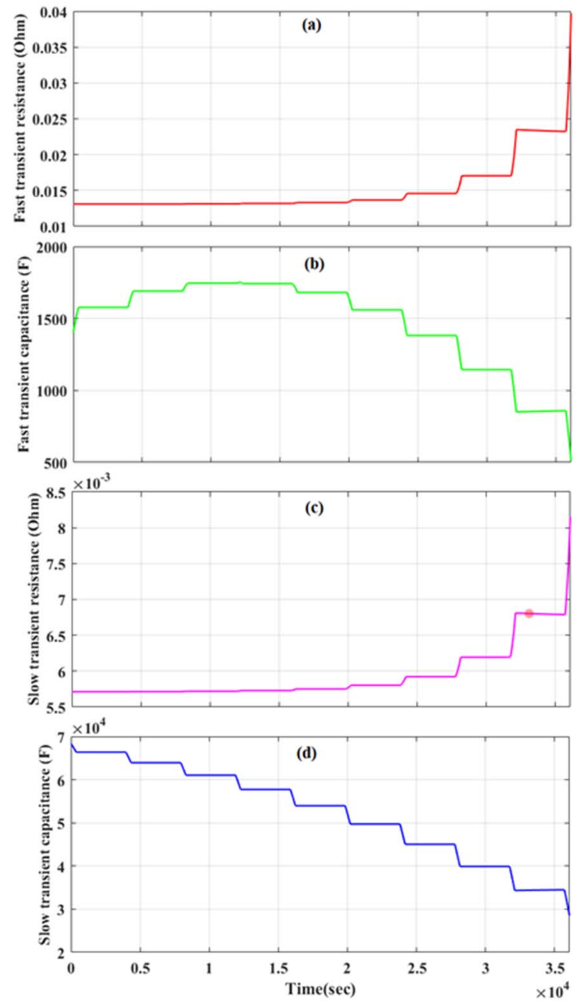

Fig. 6: Online model parameters of Li-ion cell in the PD test.

V. CONCLUSION

This paper presents a state of charge (SoC) estimation method of Li-ion batteries, considering the effects of the operating temperature on model parameters and adaptive estimation of voltage and current sensor measurement error. It is found that the transient resistances and capacitances of the Thevenin based battery model are most sensitive at the varying operating temperatures. Those model parameters are estimated in real-time with the proposed temperature-compensated battery model at varying operating temperatures. Further, this temperature compensated battery model has been used in the enhanced SoC estimation with a dual extended Kalman filter (DEKF) method. The DEKF is also used for adaptive estimation of voltage and current sensor measurement errors. The proposed SoC estimation approach has been thoroughly validated through experimental studies. Experimental results

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show that the proposed temperature-compensated battery model and adaptive estimation of voltage-current sensor measurement error ensures higher accuracy and effectiveness of the proposed SoC estimation approach.

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