State of Charge Estimation of the Lithium-Ion Battery Pack Based on Two Sigma-Point Kalman Filters

Nguyen Vinh Thuy, Nguyen Van Chi, Ngo Minh Duc, and Nguyen Hong Quang

Abstract Nowadays, the lithium-ion battery pack (LiB) is used as the main power supply for electric vehicles (EV). The remaining energy of LiB is the very important parameter determined continuously by estimating LiB's state of charge (SoC). SoC estimation is one of the main functions of the battery management systems (BMS). This article presents the use of two sigma-point Kalman filters (SPKF) to estimate accurately the SoC of the LiB based on the second-order model of the cell. The LiB's average SoC and the zero bias of the current measurement through the LiB are estimated by the first SPKF, while the second filter is applied to calculate the SoC differences between LiB's average SoC and the modules' SoC in the LiB. To improve the SoC accuracy of the LiB modules, a second-order RC equivalent circuit model (SECM) of the cell is used, and the influences of temperature, voltage hysteric, measurement errors, and zero bias of current measurement on the SoC estimation of the LiB are taken into account. To verify the method, the experimental test is conducted in the LiB with cells connected in parallels and series. The simulation and experimental results are analyzed to prove that the SoC estimation of the modules in the LiB is higher accuracy, and the LiB's average SoC errors are less than 1.5% at different temperatures ranging from − 5 to 45 °C. The calculation time consuming is shorter, and the calculation complex is reduced significantly.

Keywords Lithium-ion cell · Battery pack · Sigma-point Kalman filter · Current bias · SoC estimation · Second-order RC equivalent circuit model

1 Introduction

From the practical point of view, there are many advantages of the LiB such as higher energy density, less weight, high voltage out (about 3.7 V), safety, and fast charging/discharging rates comparing to the other kinds of battery [1, 2]. Today, the LiB is used more largely in the practice applications varying from electronics

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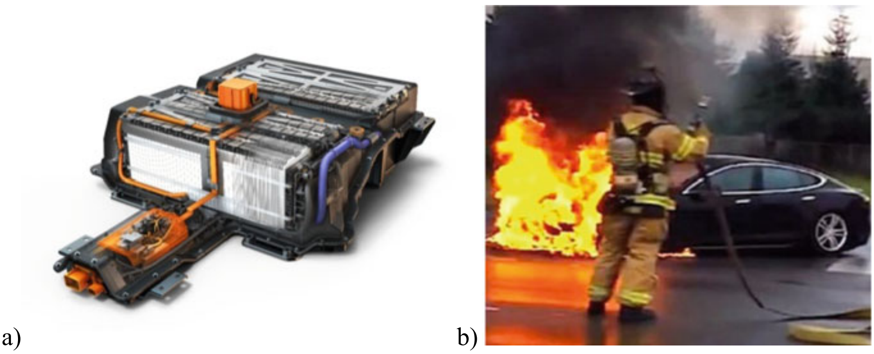
R. Kumar et al. (eds.), *Next Generation of Internet of Things*, Lecture Notes in Networks and Systems 445, https://doi.org/10.1007/978-981-19-1412-6_37

devices like laptops, mobile phones, and small power home devices to the large power electrical vehicles. LiB operation is safe in the small power devices, but when it comes to the large power and high voltage applications, the LiB is easily unsafe because the LiB is formed by ten to thousands of cells connected in series-parallel in order to supply enough power (see Fig. 1a). The cell explosion caused by overcharge/over discharge could happen in the practice (see Fig. 1b). The control problem to ensure LiB operating stably, safety, and optimally is very important. This task is conducted by the BMS. The main functions of BMS are protecting the LiB, calculating the SoC, control charging/discharging, monitoring the health and safety of the LiB, etc. The SoC is the amount of energy remaining in the battery, and it is a significant input parameter of BMS and reflects the battery performance. The SoC cannot be measured directly but can be estimated by using the cell voltage, the current of the cell, the ambience temperature, etc. The BMS uses the accurate SoC estimation as an input not only to protect LiB, prevent the LiB from overdischarge/overcharge, and improve LiB life but also to conduct the control strategies to equalize energy level of cells in the LiB and to save energy [3].

Up until now, regarding SoC estimation methods for the LiB cell, there are many approaches being used. First, methods related to the model of cells in the LiB include the methods based on open circuit voltage, coulomb counting, and impedance method [4, 5]; in the works [6, 7], authors used the cell's first-order model to estimate the SoC; and in order to improve the accuracy of SoC estimation, the hysteristic, the aging process, and the change of cell internal resistance are considered in the SoC estimation [8]. The second, methods consider to the SoC estimation algorithms as the extended Kalman filters presented in the materials [9, 10], the particle filters used in the references [11, 12], the methods using learning algorithms presented in [13, 14], the methods based on fuzzy logic and nonlinear model used in the materials [15, 16].

The SoC estimation of the LiB is the complex issue, and many research works in the literature [17–20] related to this problem have been implemented in recent years. The SoC estimation is needed to be considered not only the complexity of the



a) b)

Fig. 1 **a** The electric car battery; **b** the battery fire of Tesla Model S

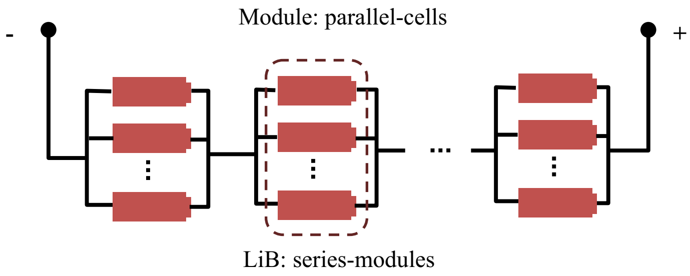


Fig. 2 Structure of the LiB

LiB's model and the complexity of the estimation algorithm but also the varying of parameters of the cell model and measurement noise.

There are many specific directions to solve the SoC estimation problem for LiB with distinct accuracy level, depending on the practical applications. To estimate the SoC of the cells in the LiB, the measurements of operating temperature, voltages, and current of the LiB are made available. In the practice, the measurements of current and voltage are affected by the noise; especially, the current is drifted by zero bias which is caused by the amplifier.

In this article, the SoC estimation method based on SPKF [21] for the LiB formed by a series of modules, each module consisted of some paralleled cells as shown in Fig. 2, is presented. This SoC estimation takes into account the noises and the zero bias of the measurements of current and voltage.

In this work, to describe the cell dynamic we use the SECM. The noises and the zero bias of the measurements of current and voltage are considered in this model. The cell dynamic is reflected more exactly in the operation condition with charge and discharge magnitude varying suddenly by using the second-order RC equivalent circuit model. The SoC estimation algorithm based on two filters is used to estimate SoC for all modules in the LiB by summing LiB's average SoC estimated by the first SPKF filter and SoC difference of modules calculated by the second SPKF filter.

The remainder of paper is organized as follows: In part 2, the dynamic second-order RC equivalent circuit model of the LiB is presented. In part 3, the SoC estimation of LiB using two filters based on the SPKF is given. Some simulations and experimental results are shown in the next part. In the last part, discussions for the paper are mentioned.

2 The Dynamic Model of the Cell and the LiB

2.1 The Second-Order RC Equivalent Circuit Model of Cell

To describe more accuracy of the dynamic of the cell, especially for the application using LiB with charge/discharge amplitude varying suddenly, the SECM model is used based on our previous work [6].

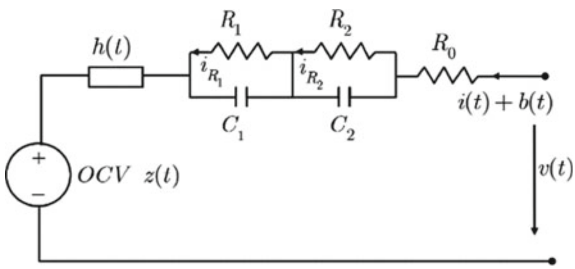
The SECM of the cell is depicted in Fig. 3. The notations in the model are as follows: two currents of two dynamic branches of the cell i_{R_1}, i_{R_2}; the hysteresis $h(t)$; SoC $z(t)$; zero bias of current of the cell $b(t)$; and$i(t)$ and $v(t)$ denote the current and the voltage of the cell, respectively. They are available by measuring and affected by noises.

In discrete-time domain, define $\underline{x}_{k+1}, \underline{u}_k, y_k$ to be the state vector, input and output vectors at the sample time k, $k = 0, 1, 2, \ldots, \infty$, respectively. They are written in Eq. (1).

$$\underline{x}_{k+1} = \begin{bmatrix} i_{R_1,k+1} \\ i_{R_2,k+1} \\ h_{k+1} \\ z_{k+1} \\ b_{k+1} \end{bmatrix}, \underline{u}_k = \begin{bmatrix} i_k \\ \text{sgn}(i_k) \end{bmatrix}, y_k = v_k \tag{1}$$

The state model of the cell is written as shown in Eq. (2):

Fig. 3 The SECM of the cell



$$\begin{bmatrix} i_{R_1,k+1} \\ i_{R_2,k+1} \\ h_{k+1} \\ z_{k+1} \\ b_{k+1} \end{bmatrix} = \begin{bmatrix} A_{R_1C_1} & 0 & 0 & 0 & 0 \\ 0 & A_{R_2C_2} & 0 & 0 & 0 \\ 0 & 0 & A_h & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} i_{R_1,k} \\ i_{R_2,k} \\ h_k \\ z_k \\ b_k \end{bmatrix} + \begin{bmatrix} \left(1 - A_{R_1C_1}\right) & 0 \\ \left(1 - A_{R_2C_2}\right) & 0 \\ 0 & (1 - A_h) \\ \frac{-\eta_k \Delta t}{Q} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} i_k \\ \operatorname{sgn}(i_k) \end{bmatrix} + \begin{bmatrix} w_{i_{R1,k}} \\ w_{i_{R1,k}} \\ 0 \\ 0 \\ w_{b,k} \end{bmatrix} \tag{2}$$

The matrices in Eq. (2) are defined as:

$$\begin{aligned} &A_{R_1C_1} = \exp\left(\frac{-\Delta t}{R_1C_1}\right), A_{R_2C_2} = \exp\left(\frac{-\Delta t}{R_2C_2}\right), \\ &B_{R_1C_1} = 1 - A_{R_1C_1}, B_{R_2C_2} = 1 - A_{R_2C_2}; A_h = \exp\left(-\left|\frac{\eta_k i_k \gamma_k \Delta t}{Q}\right|\right); B_h = 1 - A_h \\ &\quad \underline{w} = \left[\, w_{i_{R1,k}} \ w_{i_{R1,k}} \ 0 \ 0 \ w_{b,k} \,\right]^T \end{aligned} \tag{3}$$

in which $\underline{w}$ is the disturbance vector of the model formed by the current noises of two RC dynamic branches of cell $w_{i_{R_1,k}}, w_{i_{R_2,k}}$ and current bias noise of cell $w_{b,k}$. Two parameters depending on the ambient temperature of cell η_k and γ_k are the columbic efficiency.

The output equation of the SECM model is written as Eq. (4), and this equation describes the relationship between v_k and i_k, SoC, h_k, the currents of two RC branches $i_{R_1,k}, i_{R_2,k}$, and the voltage noise of cell ζ_k.

$$v_k = \mathrm{OCV}(z_k) + Mh_k - R_1 i_{R_1,k} - R_2 i_{R_2,k} - R_0 i_k + \zeta_k \tag{4}$$

Based on Eqs. (2), (3), and (4), the state space model of cell is:

$$\begin{cases} \underline{x}_{k+1} = A_k \underline{x}_k + B_k \underline{u}_k + \underline{w}_k \\ y_k = OCV(z_k) + C_k \underline{x}_k + D_k \underline{u}_k + \zeta_k \end{cases} \tag{5}$$

In the state space model (5), the matrices are formed as follows:

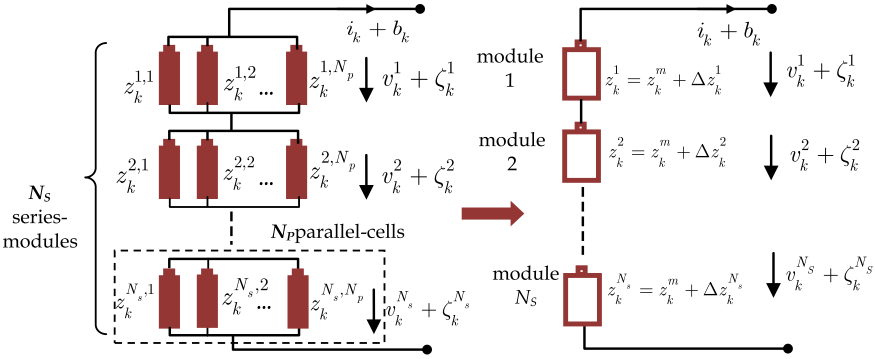


Fig. 4 The model of the lithium-ion battery pack (LiB)

$$A_k = \begin{bmatrix} A_{R_1C_1} & 0 & 0 & 0 & 0 \\ 0 & A_{R_2C_2} & 0 & 0 & 0 \\ 0 & 0 & A_h & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}, \quad B_k = \begin{bmatrix} \left(1 - A_{R_1C_1}\right) & 0 \\ \left(1 - A_{R_2C_2}\right) & 0 \\ 0 & (1 - A_h) \\ \frac{-\eta_k \Delta t}{Q} & 0 \\ 0 & 0 \end{bmatrix} \tag{6}$$

$$C_k = \left[-R_1 \ -R_2 \ M \ 0 \ 0\right], \quad D_k = \left[-R_0 \ 0\right]$$

2.2 The Dynamic Model of the LiB

The LiB is formed by some modules connected in series as described in Fig. 4. In this LiB structure, N_s is number of modules, and N_p is number of paralleled cells in the modules. The symbols of the quantities are described in Fig. 4 also.

For the paralleled cells, after a certain period of time cells's SoC will balance by itself. So the model of the LiB is transformed into the string with many modules connected in series, as plotted in Fig. 4. Demonstration of self-balance voltage and SoC of cells in one module is plotted in Figs. 5 and 6. Suppose that the initial SoCs of 6 cells vary in the range of 65–90%. The internal resistances of cells R_0 vary in the range of 1.0–1.4 mΩ. After 50 s, all six cells have the same voltage and the same SoC level.

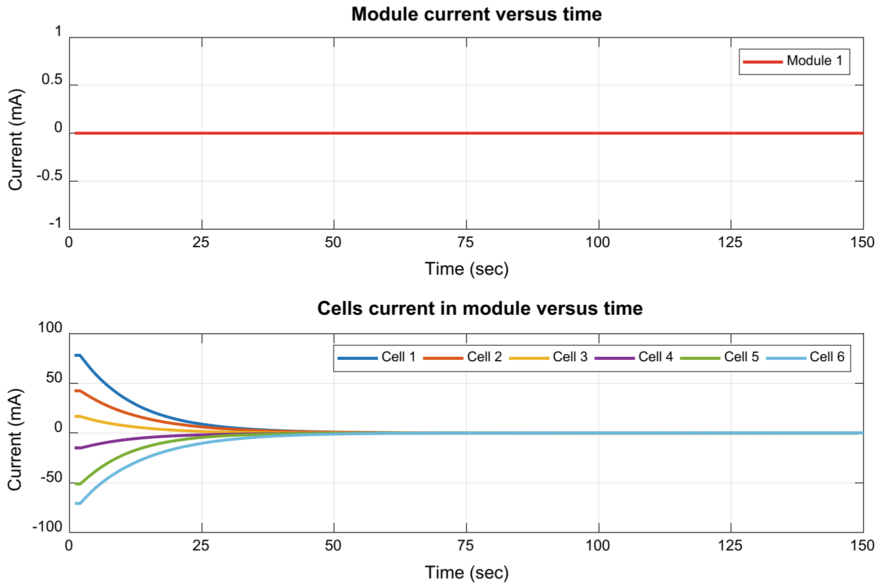


Fig. 5 **a** Current through the module, **b** current through the cells of the module

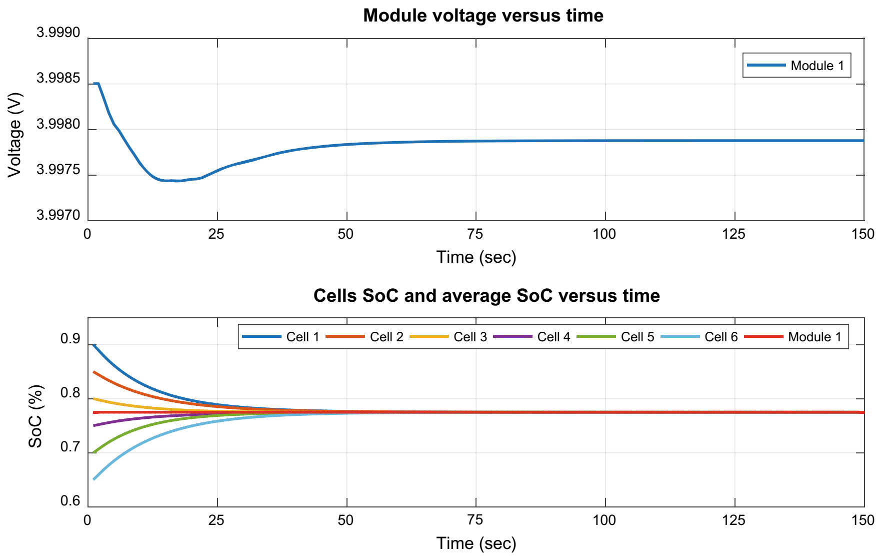


Fig. 6 **a** The voltage of the module, **b** SoC of the cells of the module

3 SoC Estimation of the LiB Using Two SPKF

The SoC estimation algorithm for the LiB using two SPKF is described as follows:

- **Step 1**: estimate the SoC average of the LiB using the first SPKF
- **Step 2**: estimate the SoC differences between the SoC average of the LiB and SoCs of the modules
- **Step 3**: The SoC of modules in the LiB is calculated by summing the SoC average (*estimated in the step 1*) and the SoC differences (*estimated in the step 2*)

To implement step 1, consider the LiB to be an equivalent cell that has the second-order RC equivalent circuit model as presented in Eq. (5). State variables need to be estimated at every sample times k are the two currents $i_{R_1}(k)$, $i_{R_2}(k)$ of two dynamic branches RC of the equivalent cell, the voltage hysteretic $h(k)$, the module's SoC $z(k)$, and the current's zero bias of $b(k)$.

The model input is the current of the LiB, it is affected by zero bias and measurement noise, and the output of the model is the sum of the voltages of modules in the LiB. We use the state vector formed as following equation:

$$\underline{x} = \left[\, i_{R_{1,k}} \; i_{R_2} \; h_k \; z_k \; b_k \,\right]^T \tag{7}$$

Define the notes $\sigma_{\tilde{x}}$, σ_w, and σ_ζ as covariance matrices of state estimation errors, systems noises, and voltage noise, respectively. The SoC estimation algorithm for the LiB is presented as following part.

State of Charge Estimation Algorithm for the LiB

Initialize the parameters of LiB
Initialize $\mathrm{SoC}_0 \in R^{(N_s \times N_p)}$, $R_0 \in R^{(N_s \times N_p)}$
Initialize $\sigma_{\tilde{x}}$, σ_w, and σ_ζ
Calculate $\overline{z}_0^{(i)}$, $\overline{R}_0^{i}$, and Q^i
For$k = 1$ **to** ∞ **do**

Measure i_k, v_k, T_k
Do step 1: Estimate $\overline{z}_k$ by the first filter
For $i = 1$ to N_s do

Do step 2: Estimate $\Delta\hat{z}_k^{(i)}$ of module ith by using the second filter

End
Do step 3: Calculate $\hat{z}^{(i)} = \hat{z}_k + \Delta\hat{z}_k^{(i)}$, $i = 1, 2..., N_s$

End

4 Experimental SoC estimation results

In this study, the SoC estimation algorithms are coded in MATLAB software. The LiB is formed by seven serial modules; each module consists of six SAMSUNG ICR18650-22P paralleled cells. The technical parameters of cell are shown in the Table 1. The experimental system is depicted in Fig. 7. The SoC estimation is conducted with the LiB with a scenario of charge/discharge varying continuously in 1 h and current amplitude changing suddenly, and the maximum of discharge/charge current amplitude are 10 A and 3 A, respectively. The scenarios of charge/discharge in this test simulate the charge/discharge situations of LiB used in the EV in the practice. Suppose that the zero bias of the current $b(k)$ of LiB varies in the range of 0.1–0.5 A.

The current of the LiB in the charge/discharge scenarios is plotted in Fig. 8. The voltages of the modules in the LiB are shown in Fig. 9, and SoC varying by the time of the modules is described in Fig. 10. Figure 11 is the varying of the voltages and

Table 1 The technical parameters of LiB SAMSUNG ICR18650-22P

Item	Specifications
Model	ICR18650-22P
Nominal capacity	2150 mAh
Minimum capacity	2050 mAh (0.2 °C discharge, 2.75 V discharge)
Charging voltage	4.2 $\pm$ 0.05 V
Nominal voltage	3.62 V (1 °C discharge)
Charging current	1075 mA
Max. charge current	2150 mA
Max. discharge current	10 A (continuous discharge)
Discharge cut-off voltage	2.75 V
Operating temperature	Charge: − 10 to 50 °C; discharge: − 20 to 70 °C

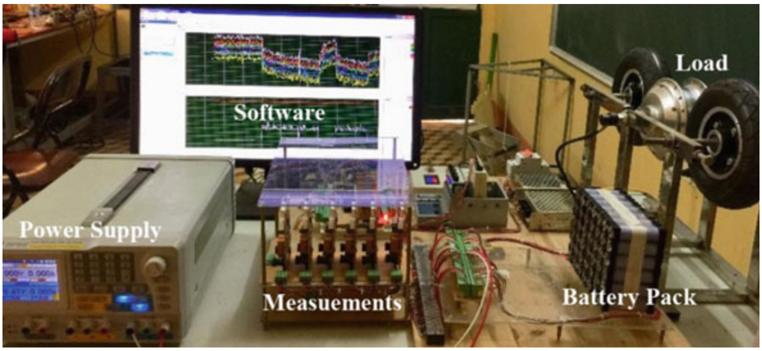


Fig. 7 Setup of the experimental system (A4 building, RIAT, TNUT)

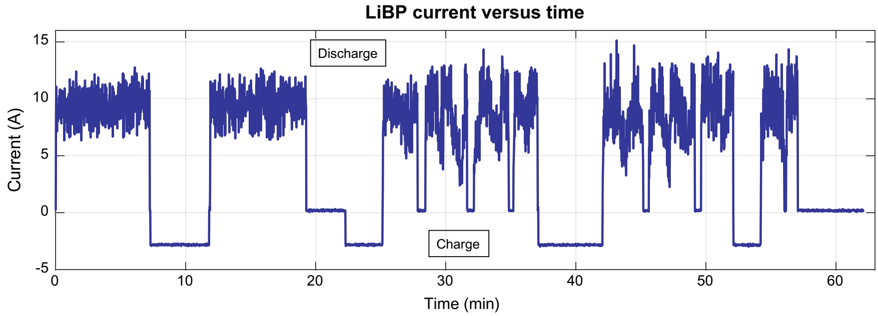


Fig. 8 The scenario of the discharge/charge current of the LiB

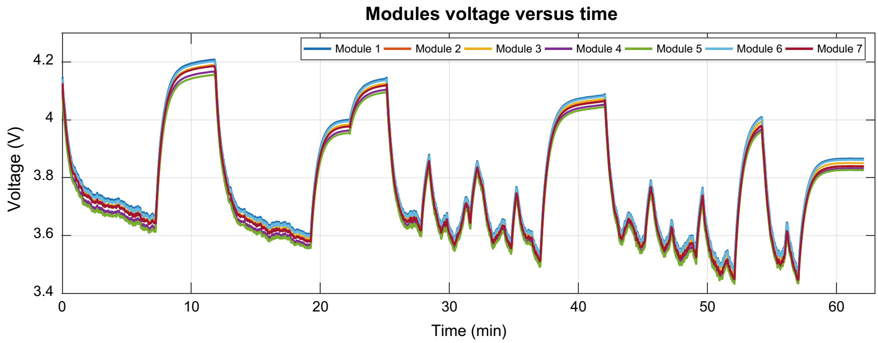


Fig. 9 The voltages of the modules in the LiB

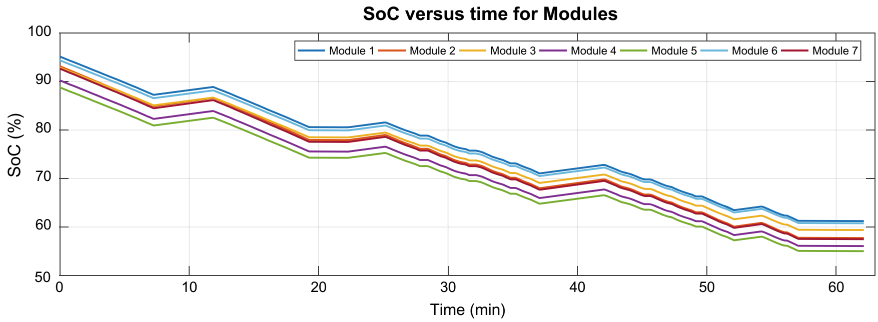


Fig. 10 The SoC varying by the time of the modules

currents of the cells in the module. The current of the 6 cells has the same rule as the current of the LiB, and the current of the LiB is equal to the total current flowing through all the cells.

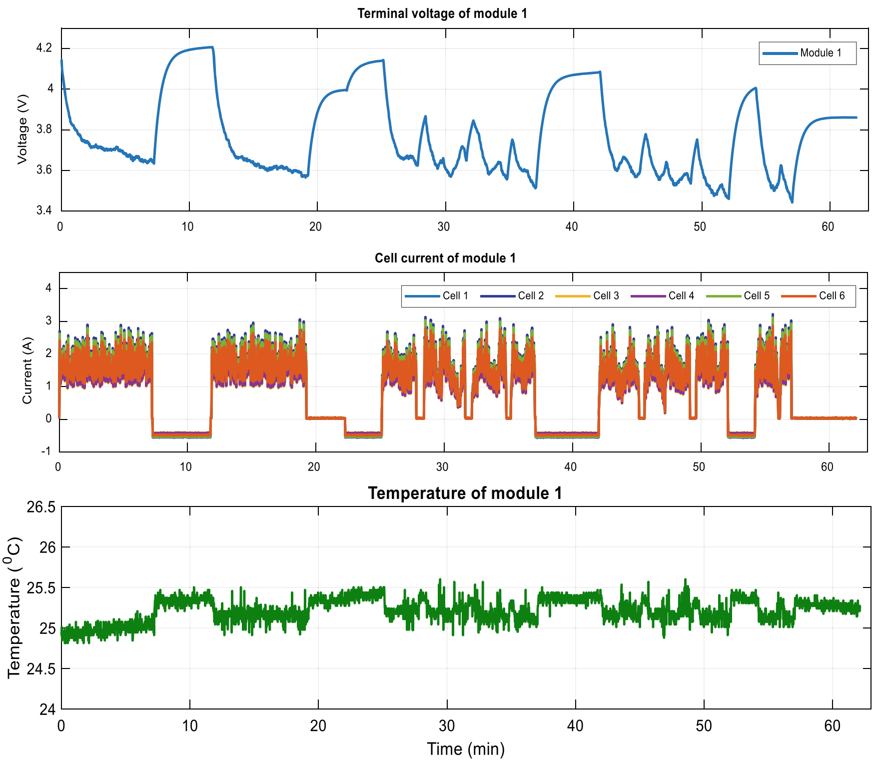


Fig. 11 The varying of the voltage and the currents of the cells in the module

Table 2 Model's dynamic parameters of the cell

T °C	– 5 °C	5 °C	15 °C	25 °C	35 °C	45 °C
η_k	1.0869	0.9803	1.0220	1.0183	1.0542	1.0399
Q (Ah)	2.1596	2.1877	2.1943	2.1507	2.1515	2.1523
γ	250.000	78.4915	63.6762	2.0748	170.6407	151.3064
M (V)	0.0347	0.0257	0.0188	0.0177	0.0201	0.0185
M_0 (V)	0.0072	0.0049	0.0048	0.0018	0.0036	0.0024
R_0 (Ω)	0.0013	0.0013	0.0012	0.0012	0.0012	0.0011
R_1 (Ω)	0.0204	0.0203	0.0201	0.0019	0.0019	0.0019
R_2 (Ω)	0.0494	0.0376	0.0288	0.0443	0.0136	0.0134
R_1C_1 (s)	0.6124	1.7555	0.3227	1.4881	0.2997	0.4630
R_2C_2 (s)	3.9035	7.5994	8.1118	36.8543	5.1840	6.5319

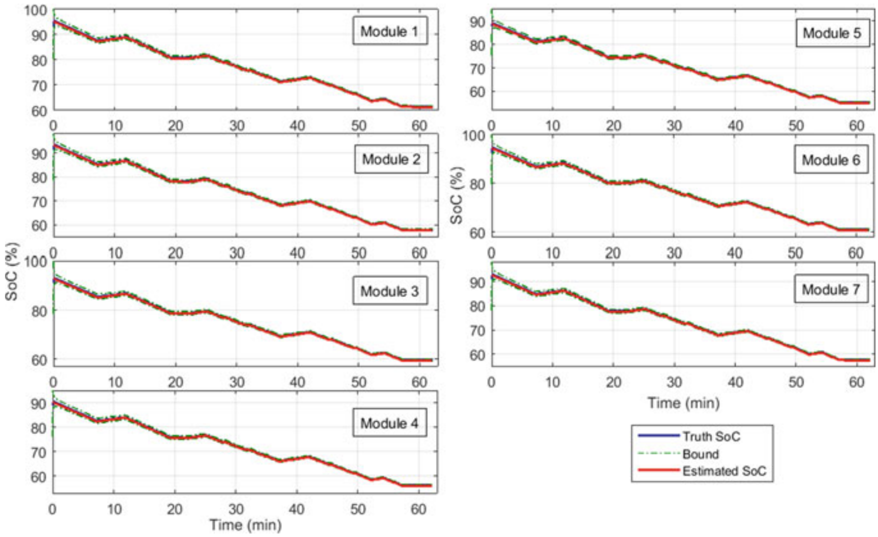


Fig. 12 The results of SoC estimation for the modules in the LiB

The dynamic parameters of the cell are given in Table 2. The initial parameters of the LiB determined at $T = 25\,°\mathrm{C}$ are $\mathrm{SoC}_0 \in R^{(N_s \times N_p)}$, $R_0 \in R^{(N_s \times N_p)}$, and $Q_0 \in R^{(N_s \times N_p)}$. The covariance matrices are:

$$\sigma^{+}_{\tilde{x},0} = \begin{bmatrix} 0.001 & 0 & 0 & 0 & 0 \\ 0 & 0.0001 & 0 & 0 & 0 \\ 0 & 0 & 0.01 & 0 & 0 \\ 0 & 0 & 0 & 0.01 & 0 \\ 0 & 0 & 0 & 0 & 0.01 \end{bmatrix}, \sigma_{\tilde{w}} = \begin{bmatrix} 0.001 & 0 \\ 0 & 0.001 \end{bmatrix}, \sigma_{\tilde{v}} = 0.0001$$

The estimated average SoC for each module in the LiB is depicted in Fig. 12, and the SoC estimation error of the modules is shown in Fig. 13. The estimated SoC shows that the SoC estimation of the modules when considering the zero bias of the current of the LiB has been tracked to the actual SoC average of the LiB with the estimated SoC error in the test is quite small, about 0.28% for each module.

The estimated current's zero bias of LiB is plotted in Fig. 14. The real values of zero bias are set as 0.1 A, 0.3 A, and 0.5 A, respectively. After a period of time $t =$ 2 min, the estimated zero bias tracks up to the real value and it is distributed around the real value of zero bias. The average value of the estimated zero bias in the test is 0.102 A, 0.306 A, and 0.484 A, respectively, with the errors of 2.0%, 2.0%, and 3.2%. These are quite small errors, so this test shows that the estimation of zero bias is suitable for practical applications.

The SoC estimation results and estimated errors for module 1 as shown in Fig. 15 when the zero bias of the LiB current varying from 0.0 A to 0.5 A at the operation

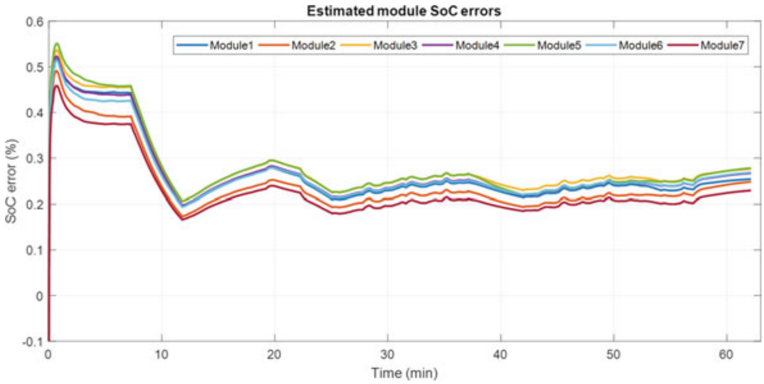


Fig. 13 The results of SoC estimation errors of the modules in the LiB

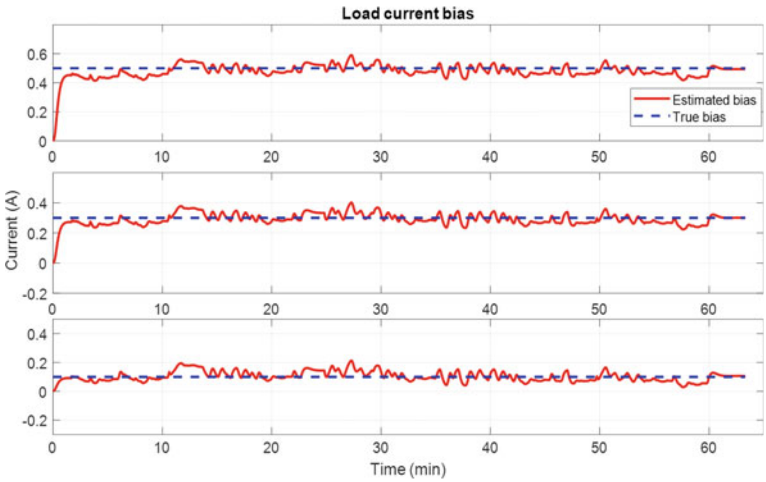


Fig. 14 The estimated result of the zero bias of the current of LiB

temperature $T = 25$ °C. The comparison of the SoC estimation errors of the LiB over the experimental period is illustrated in Table 3.

Figure 16 shows the SoC estimation error of the modules in the LiB according to the operating temperature at $T = [-5\ °C \div 45\ °C]$ with the zero bias = 0.3 A. From the above of the SoC estimation results, it shows that the estimation errors of the modules in LiB are small; in another word, the estimation of SoC has high accuracy. In the temperature ranging from – 5 to 45 °C, the SoC estimation errors of the modules are less than 1%. When the working temperature of the LiB is decreased to – 5 °C, the SoC estimation errors of the modules have an increasing tendency, but the largest error value is less than 2.3% and the average error value is about 1.5%.

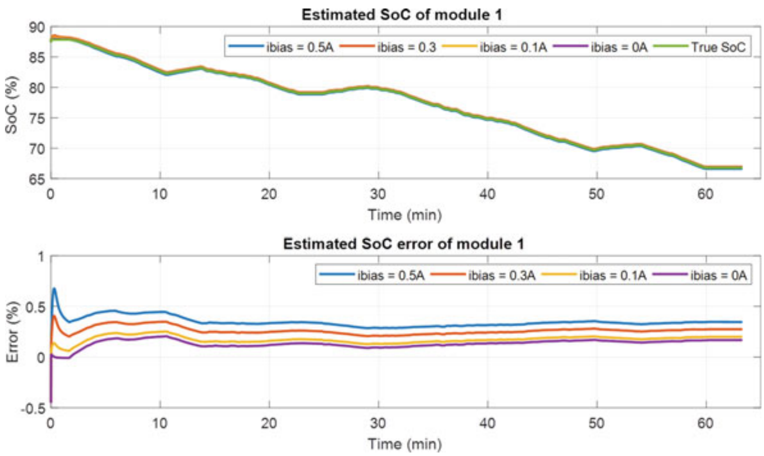


Fig. 15 The SoC estimation results and estimated errors for the module 1

Table 3 The comparison of the SoC estimation errors with respect to values of the zero bias of current of the LiB

I bias (A)	SoC error (%), $T = 25$ °C						
	Module 1	Module 2	Module 3	Module 4	Module 5	Module 6	Module 7
$b_k = 0.0$	0.12	0.10	0.12	0.11	0.14	0.11	0.12
$b_k = 0.1$	0.21	0.20	0.22	0.21	0.24	0.20	0.21
$b_k = 0.3$	0.39	0.38	0.40	0.40	0.43	0.38	0.40
$b_k = 0.5$	0.57	0.56	0.59	0.60	0.63	0.56	0.59

This is a very important SoC estimation error for the SoC estimation problem for the LiB in EV applications.

5 Conclusion

This paper presented a method to improve the SoC estimate accuracy for a LiB including many cells that are connected in series and parallel. This study uses two filters based on the SPKF algorithm to design the SoC estimation method for the LiB when taking into account the effect of temperature, measurement noise, and zero bias of current of the LiB. The dynamic model of cell in the LiB is described by the SECM to reflect more accurately the nonlinear characteristics of the LiB. The SoC estimation algorithm is applied experimentally to LiB, this LiB is formed by ICR 18650-22P SAMSUNG cells in 7 serial modules, and each module consists of 6 parallel cells. The SoC estimation results for the LiB under with the temperature changing from – 5 to 45 °C show that the errors of SoC estimations for modules in

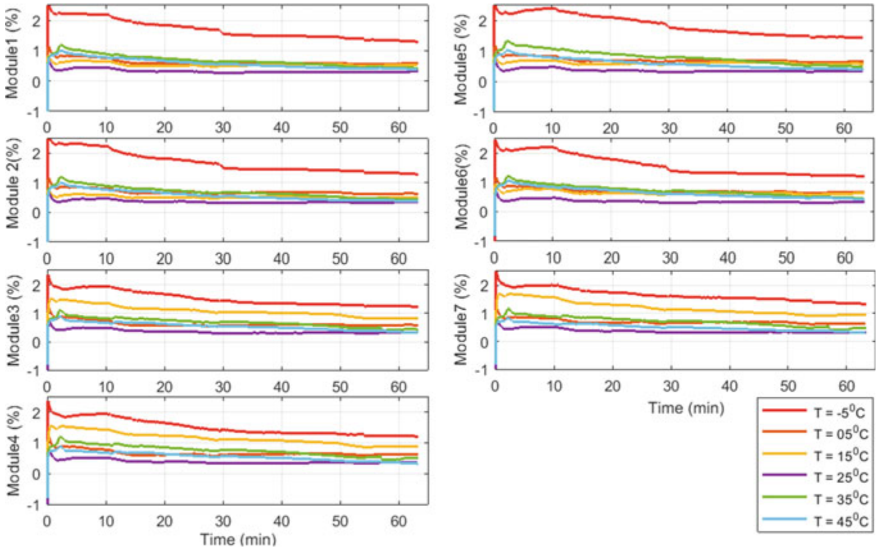


Fig. 16 The results of SoC estimation error of the modules in the LiB with respect to operating temperatures

the LiB are quite small, and the accuracy of SoC estimation has been significantly improved compared to other methods. The estimation method in this study can be applied to the SoC estimation problem for the LiB with a large number of cells. The calculation complex is reduced. This result is significant when the LiB for EV today is made by thousands of cells. Our future work focuses on improving the accuracy of the current zero bias estimation of the LiB.

Acknowledgements This research was financially supported in T2020-B12 project by Thai Nguyen University of Technology—TNUT.

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