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Lithium-Ion Battery Modelling and Adaptive Extended Kalman Filter Implementation for BMS Application Software Development

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Abstract- A custom lithium-Ion battery was built for the payload system on a single-engine two-seaters glider. The stages of software development in forming the Battery Management System as a way to provide security in the charging and discharging processes need some parameters to indicate the conditions of the battery. Therefore, in this study, the process of the State of Charge estimation which used in the Electrical Equivalent Circuit Methods and Adaptive Extended Kalman Filter was carried out in a 42 Ah Li-ion battery. As the results, a Mean Absolute Error, and a Root Mean Square Error in which the value of less than 1%. In the actual process, the real error value has never been discovered. The noise is given to determine the adaptive ability between the extended Kalman Filter and the Adaptive Extended Kalman Filter (AEKF) algorithms. In addition, the primary SoC is set at a certain value to see the estimation accuracy. The investigation shows that this method is possible to be applied in the development of the BMS software for payload systems.

Keywords BMS, payload, Lithium-ion, SoC, EECM, and AEKF.

Acronym definition

AEKF	Adaptive Extended Kalman Filter
BMS	Battery Management Systems
BTS	Battery Testing System
CCM	Coulomb Counting Method
DEKF	Dual Extende Kalman Filter
DST	Dynamic Stress Test
FDEKF	Finite Difference Extended Kalman Filter
FUDS	Federal Driving Urban Driving Schedule
ECM	Electrochemical Model
ECIM	Electrochemical Impedance Model

EECM	Electrical Equivalent Circuit Method
EKF	Extended Kalman Filter
EM	Empirical Model
EPA	Environmental Protection Agency
IAEKF	Improved Adaptive Extended Kalman Filter
KF	Kalman Filter
MBM	Model Based Method
DDM	Data Driven Model
MAE	Mean Absolute Error
MLM	Machine Learning Model
OVCM	Open Voltage-Circuit Method
RC	Resistor Capacitor
RMSE	Root Mean Square Error
USABC	US Advanced Battery Consortium
UDDS	Urban Dynamometer Driving Schedule
UKF	Unscented Kalman Filter

1. Introduction

The development and research in the Battery Management System (BMS) attempts to obtain power requirements of the electrical components of an airborne vehicle [1,2]. The need for electrical power for the payload is urgent considering the aircraft that cannot be able to provide an additional electrical energy for the Synthetic Aperture Radar (SAR) system [3]. Hence, a special additional battery for this system was developed by implementing a supply to the payload system.

1.1 Literature Review

Battery powered electronic devices have become a necessity in modern life. The need for portable battery technology is growing rapidly. Therefore, there occurred a demand of this kind of battery which requires battery management features. The features are including the monitoring of battery capacity, the time information when the system is active, the cycle calculation of the time of charging-discharging, the protection for the battery from overcharging and discharging, the storage of power data, the control on battery thermal temperature, and so on [4]. The device technology is called the Battery Management System (BMS). In addition, the BMS is needed to provide a high-precision energy to each part of the sub-system to approach the perfection of the system performance. [4,5]. One of the important functions of BMS is recognizing the State of Charge (SoC). SoC is used to determine battery capacity [6]

Several researchers have categorised the SoC value approach methods [7,8,9,10], namely, the coulomb counting (CCM) method, the open-circuit voltage method, the model-based method (MBM), and the machine learning method (Machine Learning/MLM). MBM can be implemented in real time, in a complex and accurate way. There are 2 (two) steps carried out with the MBM, the first is to model the battery and the second is to implement the algorithm [10].

Fig. 1. Stemme S15 aircraft, a single-engine two-seaters glider.

Batteries are composed of chemical substances, in which the chemical reactions and physical phenomena provide a complex set of mathematical models for estimating the SoC [12].

Modelling a battery depends on several different parameters for different types of batteries [12]. There are several types of batteries available, as described in [10], it can be seen that, lithium-ion batteries have a higher energy density and specific energy than other batteries [14]. This battery also has high reliability and efficiency, as well as a longer life span [10].

DDM requires a large amount of data and requires an extensive computational process and requires bigger data memory [8, 16]. The method that is often used in the Lithium Battery Modelling process is the EECM. Compare with the ECM and the ECIM, the EECM uses basic electronic components to represent the terminal voltage under the current profile and is often used in real time measurements [16]. Another advantage of this method is its adequate accuracy combined with an easy structure that makes the computation lighter [16]. There are several manufacturing companies and BMS companies are ones which are using the EECM method; just like what is shown in [10], therefore, it can be explained that this method can be applied in BMS devices.

It was mentioned earlier that the MBM is carried out in two stages and the first stage is by modelling the lithium battery with the EECM method while the second step is to implement the algorithm. This implementation is carried out because the empty battery level cannot return to its original condition at the processes of charging and discharging in its actual state [17]. Thus, by using a control structure, the implementation of the algorithm is used to determine the SoC value precisely and robustly [18].

The CCM implementation method is quite easy to do, but it depends on the inconsistent SoC initial conditions. Open Voltage-Circuit Method (OVCM) is the easiest method, but it is not appropriate for the dynamic SoC approach [19]. Meanwhile, MLM requires high computation and larger data memory [20]. Therefore, the MBM derivative method in the form of the Kalman filter algorithm is used in approaching the SoC value because of its efficiency in evaluating computations directly in the system [21]. In addition, this algorithm is easy to implement and it has the optimal performance and high resilience in the SoC approach [22]. SoC estimation tends to be non-linear which makes many researchers approach for the SoC value with the Kalman Filter (KF) algorithm and its relatives such as the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) [10, 23]. KF has good accuracy and is implemented on the linear data and required relatively faster computations, while the EKF and the UKF algorithm have better accuracy than the two previously mentioned algorithms. Despite the fact that the UKF has the best accuracy, the EKF, on the contrary, has advantages in data processing speed and for that reason it is more practical in determining the SOC.

Research on a battery modelling using the EECM with the EKF algorithm and it is derivative can be seen in Table 1. The data used for testing to form the model and the SoC approach algorithm consists of variable data that varies in data experiments of 180 Ah from Battery Testing System (BTS) [28], the Federal Driving Urban Driving Schedule (FUDS) and the UDDS. FUDS is a voltage discharge for 1400 seconds which is a standard test under the US Advanced Battery Consortium (USABC) to see the performance and testing of electric vehicle batteries [32], while the Dynamic Stress Test (DST) has a shorter time interval and a simpler form test procedure [33, 34]. Urban Dynamometer Driving Schedule (UDDS) is a test procedure refers to U.S Environmental Protection Agency (EPA). More details are explained in [35].

The algorithm approach used here is the EKF and several derivative additional methods which are applied to improve the SoC estimation. This can be seen in Table 1, where it shows that by using the EKF algorithm, the error in average showed range of around 2%. The noise that presents from the system, will add to a higher deviation and noise, therefore Adaptive Extended Kalman Filter utilized [24] and this algorithm also has a minor error compared to the EKF. For that reason, the AEKF is applied in this study.

In this study, lithium-ion battery modelling will be carried out using the EECM method and the AEKF algorithm in carrying out the SoC approach as a part of the BMS software design for a payload system on the aircraft.

1.2 Contributions

In the integration of custom batteries for aircraft payload systems, scenarios and analysis are important providing safety distribution power to the payload system, because the load dynamics that occur especially when the payload system runs with an undivine load. It is necessary to have a certain method to filter the battery performance in simulation to nearly show the real conditions.

Therefore, the main objective of this contribution is to learn reliability and robustly the AEKF can estimate SoC under different disturbance.

Table 1. Methods and algorithms used in the SoC approach

Ref.	Year	Model EECM	Algorithm	Estimation Data	Error	Data Type
[24]	2013	1RC	AEKF	Arbin battery test system BT2000	< 2%	UDDS
[25]	2014	2RC	FDEKF	12Ah Digatron MCT 30-05-40 cell	2%	DST
[26]	2021	1RC	IAEKF	MATLAB	±2%	FUDS
[27]	2020	1RC	AEKF	MATLAB	< 2%	BST and UDDS
[28]	2013	2RC	EKF	MATLAB	1.9-2.7%	BTS180Ah
[29]	2016	2RC	DEKF	MATLAB	-	Experiment data with multi Maccor battery Tester
[30]	2021	2RC	DFFAEKF	MATLAB	0.85%	BTS 4000
[31]	2021	2RC	IAEKF	MATLAB	<2%	Experimental instruments consist of programmable STM32F407 and IT6722 DC power supply

2. Lithium-Ion Battery Modelling and Parameter Identification

EECM uses basic electronic components in presenting the battery and first RC model has a simpler structure and better accuracy [36], therefore the researchers chose to model the 42 Ah Lithium Battery. Figure 2 illustrates the structure, where U_{OCV} is representing an ideal voltage source and resistance R_p together with capacitor C_p which is representing them to follow the transient transpose while in charging or discharging processes [37].

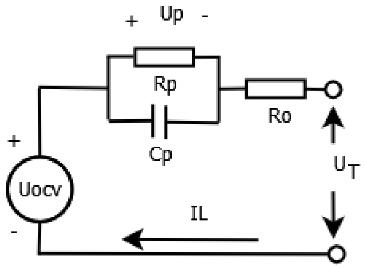

Fig. 2. Electrical Equivalent Circuit Model Lithium-Ion Battery

The R_o in the picture shows the internal resistance. U_T, U_p and I_L represent terminal voltage, polarization voltage and loading current. The state space equation model can be written as Eq. (1)

$$\begin{cases} \dot{U}_p = -\frac{1}{C_pR_p}U_p + \frac{1}{C_p}I_L \\ U = U_{ocv}(SoC) - U_p - I_LR_o \end{cases} \tag{1}$$

The discrete model from Eq. (1) can be expressed as Eq. (2)

$$\begin{cases} U_{p,k} = U_{p,k-1}exp\left(-\frac{T_s}{C_pR_p}\right) + \\ \qquad I_{L,k-1}R_p\left[1 - exp\left(-\frac{T_s}{C_pR_p}\right)\right] \\ U_{T,k} = U_{OCV}(SOC_k) - U_{p,k} - I_{L,k}R_o \end{cases} \tag{2}$$

Ts is the sampling time interval of the parameter estimator, that is set to 0.4 s toward k and k-1 are the time steps.

Parameter identification used recursive least square methods for reaching a better accuracy in determining new observation data [38]. Therefore, from Eq. (2), a further following step of $U_{T,k}$ can be obtained as Eq. (3)

$$U_{T,k} = U_{OCV}(SOC_k) - U_{p,k-1}exp\left(-\frac{T_s}{C_pR_p}\right) \\ I_{L,k-1}R_p\left[1 - exp\left(-\frac{T_s}{C_pR_p}\right)\right] - I_{L,k}R_o \tag{3}$$

Moreover, the difference between $U_{T,k}$ and U_{ocv} is expressed by V_T and can be written as Eq. (4)

$$V_{T,k} = -U_{p,k-1}exp\left(-\frac{T_s}{C_pR_p}\right) + I_{L,k-1}R_p\left[1 - exp\left(-\frac{T_s}{C_pR_p}\right)\right] - I_{L,k}R_o \tag{4}$$

Furthermore, $U_{T,k-1}$ can be obtained from the following;

$$U_{T,k-1} = -U_{p,k-1} - I_{L,k-1}R_o \quad (5)$$

The correlation between $U_{p,k}$ and $U_{p,k-1}$ can be derived as Eq. (6)

$$V_{T,k} = exp\left(-\frac{T_s}{C_pR_p}\right)V_{T,k-1} + (-R_o)I_{L,k} + \left\{exp\left(-\frac{T_s}{C_pR_p}\right)R_o - \left[1 - exp\left(-\frac{T_s}{C_pR_p}\right)\right]R_p\right\}I_{L,k-1} \quad (6)$$

The Eq. (6) can be rewritten as Eq. (7)

$$V_k = a_1V_{k-1} + a_2I_{L,k} + a_3I_{L,k-1} \quad (7)$$

Where the formula is represents in Eq. (8)

$$\begin{cases} a_1 = exp\left(-\frac{T_s}{C_pR_p}\right) \\ a_2 = -R_o \\ a_3 = a_1R_o - [1 - a_1]R_p \end{cases} \quad (8)$$

Then, the parameters can be achieved as Eq. (9)

$$\begin{cases} R_p = \frac{a_1a_2+a_3}{a_1-1} \\ R_o = -a_1 \\ C_p = \frac{(1-a_1)T_s}{\ln(a_1)(a_1a_2+a_3)} \end{cases} \quad (9)$$

3. SoC Estimation Definition

3.1. SoC Algorithm

The SoC is defined as a difference of full amount of capacity provide in the battery with the available capacity, which generally expressed as Eq. (10)

$$\mathrm{SoC_k} = \mathrm{SoC_{t0}} - \frac{1}{\mathrm{C_{available}}}\int_{t0}^{t}\eta_i \mathrm{I(t)dt} \quad (10)$$

When $C_{available}$ is the capacity, η_i is the coulomb efficiency and I is the battery charging/discharge current and the assumption ratio is 0.9 during charging and 1 during discharge [14]. The discrete equation for Eq. (10) can be written as Eq. (11)

$$SoC_K = SOC_{k-1} - \frac{T_s}{C_{available}}I_{k-1} \quad (11)$$

3.2. Lithium-Ion State and Measurement Equation

The observation of the state equations of the discrete system is expressed as Eq. (12)

$$\begin{pmatrix} U_{p,k} \\ SoC_k \end{pmatrix} = \begin{pmatrix} exp\left(-\frac{T_s}{C_pR_p}\right) & 0 \\ 0 & 1 \end{pmatrix}\begin{pmatrix} U_{p,k-1} \\ SoC_{k-1} \end{pmatrix} + \begin{pmatrix} \left[1 - exp\left(-\frac{T_s}{C_pR_p}\right)\right]R_p \\ -\frac{T_s}{C_{available}} \end{pmatrix}I_{k-1} \quad (12)$$

Here, $X_k = \begin{pmatrix} U_{p,k} \\ SoC_k \end{pmatrix}$ and $Y_k = U_{T,k}$, with the measurement equation formulated as Eq. (13)

$$U_{T,k} = U_{OCV}(SoC_k) - U_{p,k} - I_{L,k}R_o \quad (13)$$

3.3. Adaptive Extended Kalman Filter Algorithm

The state equation for non linier discrete-time system and the measurement system equation can be presented as follows

$$\begin{cases} X_k = \begin{pmatrix} u_{p,k} \\ SoC_k \end{pmatrix} + w_k \\ Y_k = Cx_{k+1} + Du_k + v_k \end{cases} \quad (14)$$

X_k and Y_k denotes state variable and measurement variable at time of k, The matrices C and D describe the dynamic system. Where C is the dynamic of input measurement system which is defined as $\frac{\partial g}{\partial x} = \left(-\frac{dV_{OCV}}{dX} \quad 1\right)$. Furthermore D interprete with $-R_o$. u_k represent system signal input and v_k and w_k are the system measurement noise and process noise, in which both are uncorrelated zero mean Gaussian white sequence [39].

The description of the AEKF can be illustrated as follows:

- Initialise the mean $(\overline{X_o})$ and the covariance (P_0) of the initial system state X_0

$$\begin{cases} \bar{X}_0 = E(X_0) \\ P_0 = E[(X_0 - \bar{X}_0)(X_0 - \bar{X}_0)^T] \end{cases} \quad (15)$$

Where E(.) is the expectation of the mean value.

- Time update for the state and covariance prediction.

The state prediction refers to the Equation (14)

$$\begin{cases} X_k^+ = f(X_{k-1}, u_{k-1}) + w_k \\ P_k^- = C_kP_{k-1}C_k^T + Q_k \end{cases} \quad (16)$$

- Measurement update

Kalman gain matrix

$$K_k = P_k^-C^T(CP_k^- + R_k)^{-1} \quad (17)$$

Update covariance

$$P_k = (I - K_kC_k)P_k(I - K_kC_k)^T + K_kR_kK_k^T \quad (18)$$

- Update state estimation

$$X_k = X_k + Ke_k \quad (19)$$

$$e_k = Y_k - (CX_k + D) \quad (20)$$

- Adaptive adjustment of Q and R

$$Q_k = K_kH_kK_k^T \quad (21)$$

$$H_k = \frac{1}{M}\sum_{i=k-M+1}^{k} e_ke_k^T \quad (22)$$

$$R_k = H_k - CP_kC^T \quad (23)$$

H is a correlation between the state of dynamic system and measurements defined as the measurement sensitivity matrix [40]. Q and R are the state process noise and the measurement noise [15, 26] . And M is the sliding estimation window and the number from 0 trough M [41].

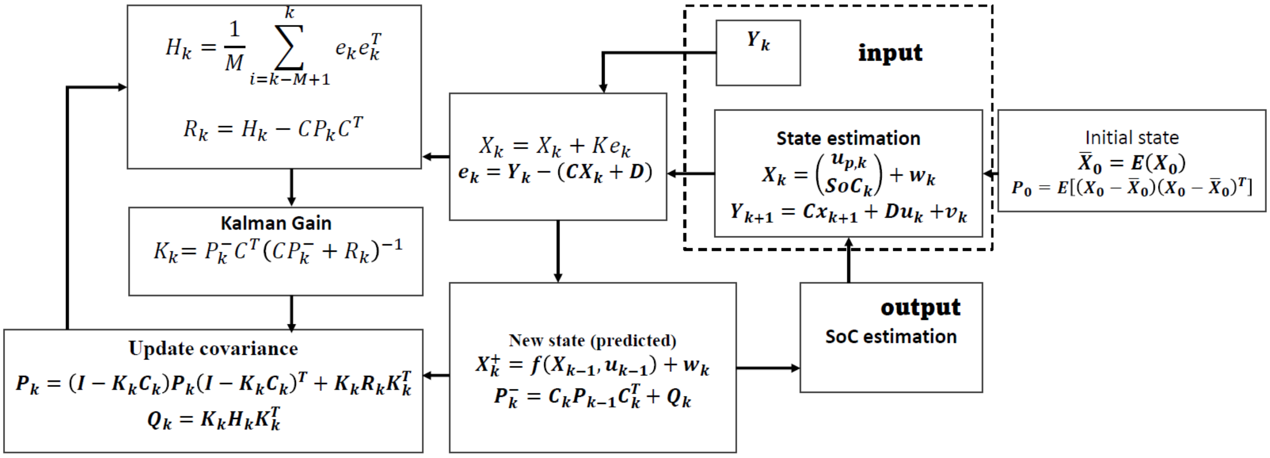

Fig. 3. Schematic scheme for AEKF algorithm

4. Experiments and Simulation results

4.1. Experiments

The experiments were conducted under room temperature of 25° C on lithium-ion batteries with capacity of 42Ah. The specification of the battery is listed in Table 2. The experimental test bench is set up as what is shown in Fig. 4, which includes the lithium-ion battery system that consist of 12 battery strings in parallel, composed of 7 cells in series and completed with sensors. The cutoff voltage is set at 19 volts to provide the battery safety; in which the SoC ranges from 0-100%, at a voltage of 19-29 volt. In addition, this experiment also employed an electronic load for the charging and discharging processes, a data acquisition card, and a computer. The data current and voltage from the sensors are recorded by the data acquisition module. The computer is used to execute instruction charge or discharge to the electronic load and also getting the data processing from the data acquisition module.

Table 2. Battery Lithium-Ion specification

Nominal Capacity	42 Ah
Voltage	29V
Current Max	20.4A
Mass	4.116 kg
Dimension	30x15.5x8.2 cm
Temperature charge max	45 °C
Temperature discharge max	60 °C

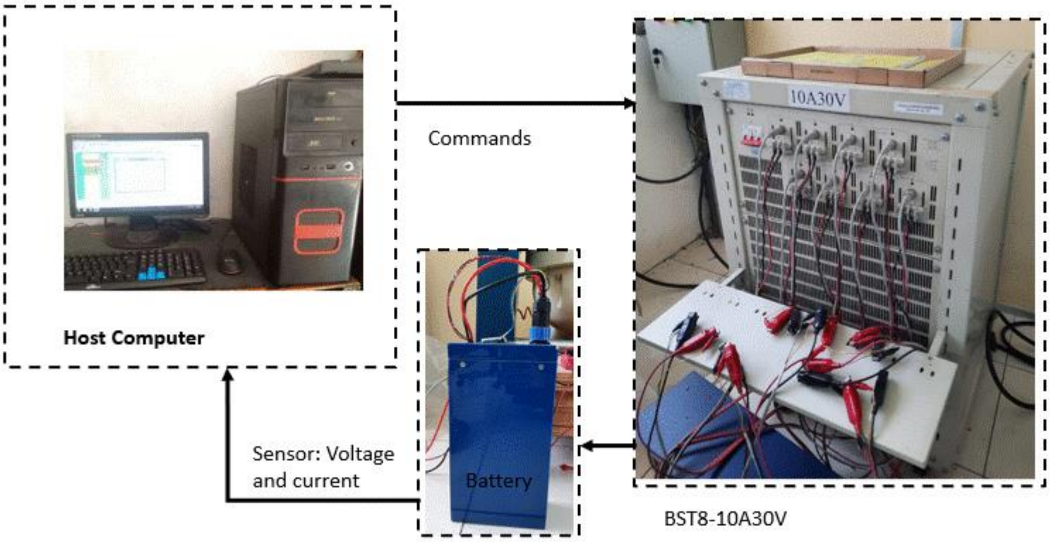

Fig. 4. Experimental battery test platform.

4.2. Battery Test

A test was performed on a lithium-ion test bench with the charged and discharged at constant current of 0.2 C from a fully charged state of 90% from the nominal capacity. The proceed would run until the voltage reaches the cut-off voltage. The current and voltage profile are presented in Fig. 5. (a) and Fig.5. (b). It can be seen from the line graph that between the charging and discharging processes are different from each other and they depend on the treatment of the process that had been given.

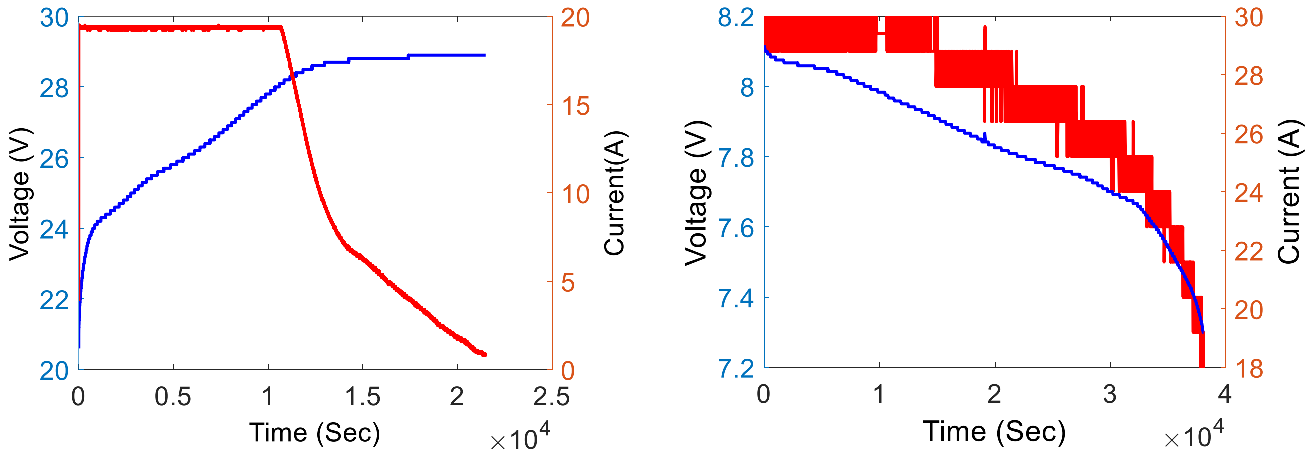

Fig. 5. Current and voltage; (a) charging and (b) discharging profile

4.2. SoC Estimation Based AEKF

In this chapter, there will be the explanation on the comparison of the estimation results using the EECM also the EKF and the AEKF algorithms. In order to establish the response of the model and algorithm to the SoC of the Lithium-ion battery, the model is simulated from real data experiment according to Section 3, and the SoC estimation can be determine from what is depicted in Fig. 6 for the charging process and Fig. 7 for the discharging process. At the time when the EKF and AEKF algorithms are used, the result shows the estimated line that is close to the real data value. The equilibrium potential is higher at the charging process than that at the discharging process, which indicates that the equilibrium potential depends on the previous treatment of the battery module. For that reason, this paper focused on the SoC estimation from discharging process.

Table 3. Statistical analysis of the SoC Estimation

Algorithm	MAE (%)	RSME (%)
AEKF	0.27	0.44
EKF	0.79	0.65

The detailed analysis of the SoC estimation accuracy is based on a mean absolute error (MAE) and a root mean square (RSME) which is provided in Table 3. The determination formulas are presented in Eq. (23) and Eq. (24).

$$MAE = \frac{\sum_{i=1}^{N}|SoC_i - \widehat{SoC_i}|}{N} \quad (24)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(SoC_i - \widehat{SoC_i})^2}{N}} \quad (25)$$

where SoC_0 and $\widehat{SoC}$ indicates the real SoC value and estimated SoC value.

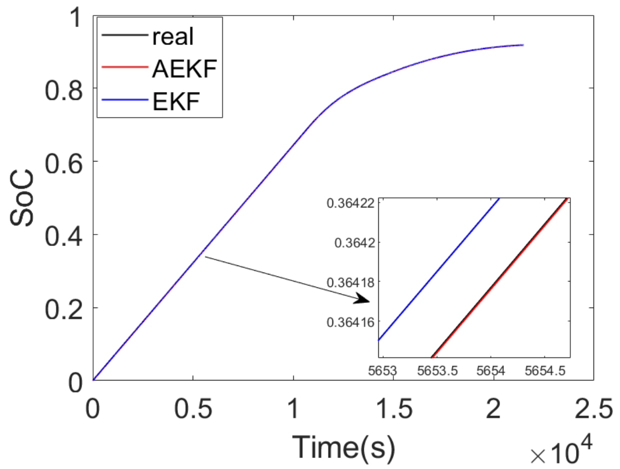

Fig. 6. SOC Estimation on Charge Process

From Table 3, it can be seen that the MAE and RSME of SoC estimate are both less than 1% from a capacity of 42 Ah. In conclusion, the proposed method and algorithm can well address the SoC prediction.

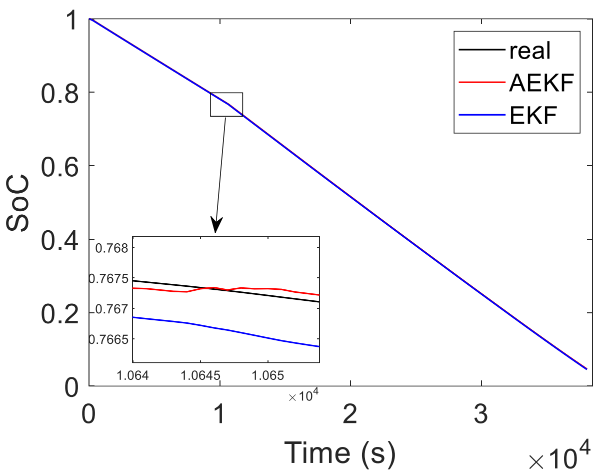

Fig. 7. SoC Estimation on Discharging Process

4.3 SoC Estimation with Statistical Noise

In order to certify the response of the purposed model, the AEKF algorithm implemented in the SoC of the battery under sophisticated application conditions. The value of noise in the actual process has never been discovered. The entanglement of the Kalman Filter and the noise covariance has greatly affected the SoC estimation value [42]. As a result, in this estimation, the value of noise convariance from the Q process and the R measurement is determined. Here, the Q is set as 10^{-2} and the R is set as 1.5. Hence, the value would be simulated to gain the SoC estimation and is used to figure out the robustness of the proposed method. From the simulation which used the EKF algorithm shows results of the noise that greatly affects the SoC estimation, and it can be seen in Fig. 8 (a) and Fig. 8. (b). Meanwhile, from the one which used the AEKF algorithm, it can be seen that the SoC estimation line could not be distorted by the given noise. As a consequence, the comparison results show that the AEKF has a better resistance to the noise.

SoC estimation on the AEKF is greatly influenced by initial parameters. Here, the initial SOC is set to 0.9, 0. 8, and 0.7. The simulation result is as shown in Fig. 9. It can be determined that the estimation method can satisfy the initial SOC errors within 50s and correctly following the SOC reference path. For this reason, the proposed estimation method has compensated robustness against imprecise initial SOC.

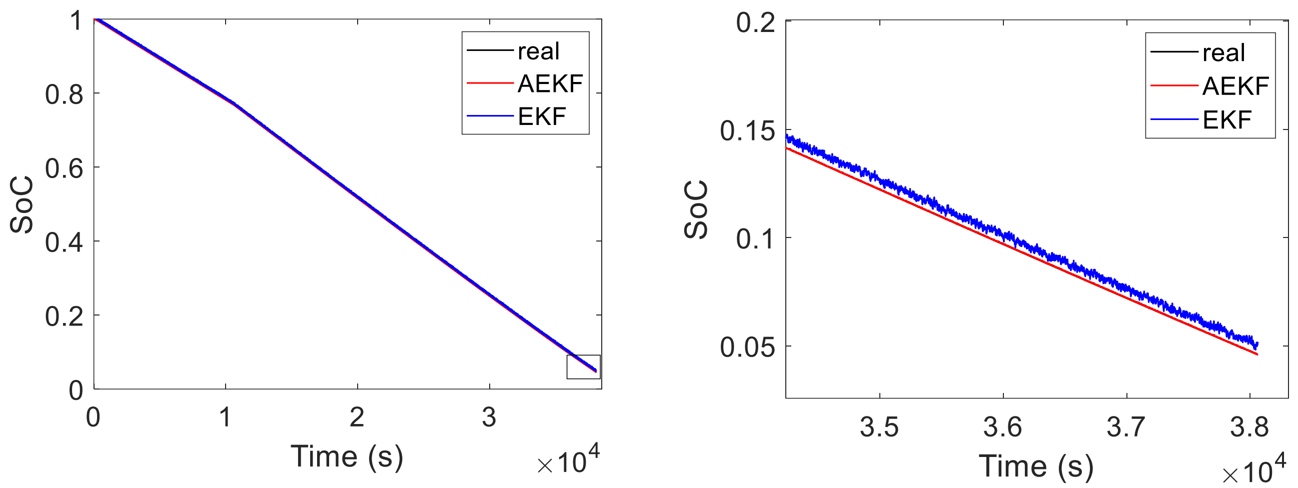

Fig. 8. SoC Estimation result with noise (a) SoC Estimation; (b) Details

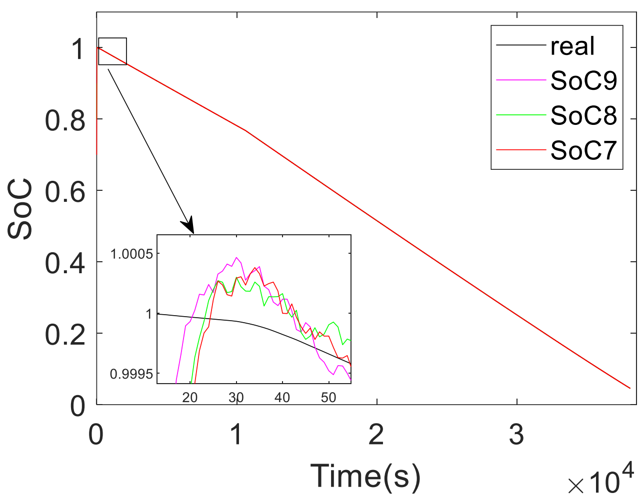

Fig. 9. SOC Estimation Based on Different Initial of SOC

5. Conclusion

The objective of this research is to implement EECM and AEKF on 42 Ah battery Lithium ion for payload system. The detailed study and remarks are described below

1) EECM and AEKF were chosen because both are lighter in computing and show a high degree of accuracy.
2) The MAE and the RSME of the SoC estimation method are both less than 1% .
3) A robustness evaluation was also conducted along with giving certain value in noise covariance process and covariance measurement. From the comparison result, it shows that the estimation on SoC with the AEKF algorithm is more persistent from noise than the EKF, furthermore, the AEKF could control the SoC estimation and it could also comply the real SoC value.
4) A treatment of different initial SoC value was also given in the simulation that could reach the satisfying initial of SoC errors within 50s and correctly following the SoC reference path.
5) The implementation of these methods and the algorithms can be conducted on the BMS software development for the payload system.

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