

A robust state of charge estimation for multiple models of lead acid battery using adaptive extended Kalman filter

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ABSTRACT

An accurate estimation technique of the state of charge (SOC) of batteries is an essential task of the battery management system. The adaptive Kalman filter (AEKF) has been used as an observer to investigate the SOC estimation effectiveness. Therefore, The SOC is a reflexion of the chemistry of the cell which it is the key parameter for the battery management system. It is very complex to monitor the SOC and control the internal states of the cell. Three battery models are proposed and their state space models have been established, their parameters were identified by applying the least square method. However, the SOC estimation accuracy of the battery depends on the model and the efficiency of the algorithm. In this paper, AEKF technique is presented to estimate the SOC of Lead acid battery. The experimental data is used to identify the parameters of the three models and used to build different open circuit voltage–state of charge (OCV-SOC) functions relationship. The results shows that the SOC estimation based-model which has been built by high order RC model can effectively limit the error, hence guaranty the accuracy and robustness.

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1. INTRODUCTION

Photovoltaic energy is the modern technology developed among the recent years due to the necessity of clean resource, safe energy with a cost reduced. The radiation of the sun flows on the solar panel, which makes the cell generate an electrical energy. The electrical energy converted from the cells is using to run stand-alone systems and many applications and also stored in the battery pack.

The conversion of the energy is an essential part in the solar systems by connecting the cells in some combination therefore to attain the necessary level of voltage and power. The battery management system is using to manage the electricity comes from solar panels, conduct operations by using different algorithms to achieve a high power whatever the radiation and the weather. Thus, it controls the charging process and manages the energy of the battery in discharge too. Therefore, it protects the whole system, controls and monitors the batteries, arranges the power between the system and the loads.

Energy storage systems are widely used in photovoltaic systems (PV), power grids, and electric vehicle. Lead-Acid batteries take over these utilizations due to its high energy and cycle of life [1]. In PV, a battery pack is a fundamental part, usually numerous battery cells connected in series or parallel, or even in mix technology hence, they employed to safeguard, ensure the operations at nights or emergency

situations. Moreover, due the differences among the cells, finding the SOC for the whole pack is necessary. To ensure its proper running and extend the life of the battery, the key task is the estimation of the current status of the battery, which knows as the state of charge (SOC). Therefore, this paper investigates on the SOC estimation for the battery. The SOC, it is the reflexion ratio of the energy remaining on the battery, cannot be directly measured as it related to the chemical of the cell [2]. This is a challenge to use a capable algorithm for accurate estimating, by using measurable inputs, including the noise of sensors, temperature, and nonlinear behaviour.

State estimation is a recent subject, but it has been well explained in the last decade for reason of electric vehicle and stand-alone emergency systems. There are numerous methods to determine the SOC [3, 4]. Current-based method (coulomb counting) [5, 6] use the equation of drawn current from the battery capacity to estimate SOC. It is a less accurate method, thus the initial SOC must be known and that is not always possible. Moreover, the accumulated current error measurement may cause inaccurate estimation. Voltage-based methods [7-9] use the relationship between open circuit voltage (OCV) and SOC. The battery has to be rested enough time to reach the equilibrium state. Therefore, the relationship suffers from changes with different effects. Model-based estimation [10-12] uses mathematical models to link measured signals, it is known to done accurate and robust estimates. It is based on the equivalent circuit models.

SOC estimation using model-based, an accurate battery model is most important; a model suitable of capturing and tracking the battery dynamics and also easy to implement. Two general types of classification; Electrochemical models [13] use the chemical equations to describe the electrochemical process, they represent the battery behaviour accurately but they are complex to implement and equivalent circuit models (ECM) [14, 15] use electrical components to describe electrochemical processes like resistors and capacitors. ECMs are commonly used due to their simplicity in implementation and accuracy of estimation.

In [16-18] proposed ECM involved of Shepherd, Unnewher and Nernst models. Other models like hysteresis and self-correcting are presented, the accuracy of these models can be improved by adding RC branches. In [19] a comprehensive study is presented with determination of the parameter. Thus, different models have been used. Among them, the second order RC model has been given well results. Since, the estimation algorithm use measurements to construct the internal states, by the usage of observers. The extended Kalman filter is the common choice to deal with nonlinear systems [20]. In three papers [17, 18, 21] Gregory Plett, presented the EKF algorithm and investigate the accuracy of SOC estimation with battery model and explained the limitation of it. In both paper; states estimation with time varying parameters gave good results. Also SOC estimation using Kalman filter is investigated in [22-24] showed performance however the scenarios, also the unscented Kalman filter [25] (UKF) performs relatively better. In [19] the comparison between 18 different Kalman filter showed the dual EKF was found to perform the best.

This paper investigates of the SOC estimating for a lead acid battery with adaptive Kalman filter. The battery model is critical for SOC estimation, therefore three model namely first order equivalent circuit, second order and third order model are considered, combined with four OCV-SOC functions in term to modelling accuracy. The paper is organized as follows: Section 2 introduces the battery models. In section 3, the method has been used to identify models parameters, the AEKF algorithm briefly introduced while this is followed by experiment results and analysis. Finally, conclusions of the paper are given in section 5.

2. BATTERY MODELLING

In order to apply a model based to achieve an accurate SOC estimation, firstly, a battery model should be designed and constructed. Thus, equivalent circuit model (ECM) equations required to build and estimate the parameters and the states. Therefore, , numerous types of battery models have been used to describe the dynamics of the battery were presented and evaluated [1]. To reach excellent capture between the output voltage and the characteristics of the battery considering the complexity of computation and speed response, three models has been selected as illustrated in Figure 1.

The first order model consists of an open circuit voltage (OCV), a series resistance R_s represents the internal resistance of the cell which denotes the resistivity of the electrolyte, the separator and electrodes. In addition to a parallel branch of resistance and capacitance polarization connected in series. While, the second order model contains two RC branches and the third order model contains three RC branches. I_L expresses the load current (it takes negative for charge, positive for discharge), V_t indicates the terminal voltage. The OCV is used to denote the internal voltage source of the battery. The electrical behaviour of three proposed model a,b and c can be written in (1), (2) and (3) respectively:

$$\text{Model (a)} \quad \left\{ \begin{array}{l} \frac{dV_1}{dt} = \frac{-V_1}{R_1 C_1} + \frac{I_L}{C_1} \\ V_t = OCV(z) - I_L R_0 - V_1 \end{array} \right. \quad (1)$$

$$\text{Model (b)} \quad \left\{ \begin{array}{l} \frac{dV_1}{dt} = \frac{-V_1}{R_1 C_1} + \frac{I_L}{C_1} \\ \frac{dV_2}{dt} = \frac{-V_2}{R_2 C_2} + \frac{I_L}{C_2} \\ V_t = OCV(z) - I_L R_0 - V_1 - V_2 \end{array} \right. \quad (2)$$

$$\text{Model (c)} \quad \left\{ \begin{array}{l} \frac{dV_1}{dt} = \frac{-V_1}{R_1 C_1} + \frac{I_L}{C_1} \\ \frac{dV_2}{dt} = \frac{-V_2}{R_2 C_2} + \frac{I_L}{C_2} \\ \frac{dV_3}{dt} = \frac{-V_3}{R_3 C_3} + \frac{I_L}{C_3} \\ V_t = OCV(z) - I_L R_0 - V_1 - V_2 - V_3 \end{array} \right. \quad (3)$$

Where z denotes the state of charge attached to each polarization voltage.

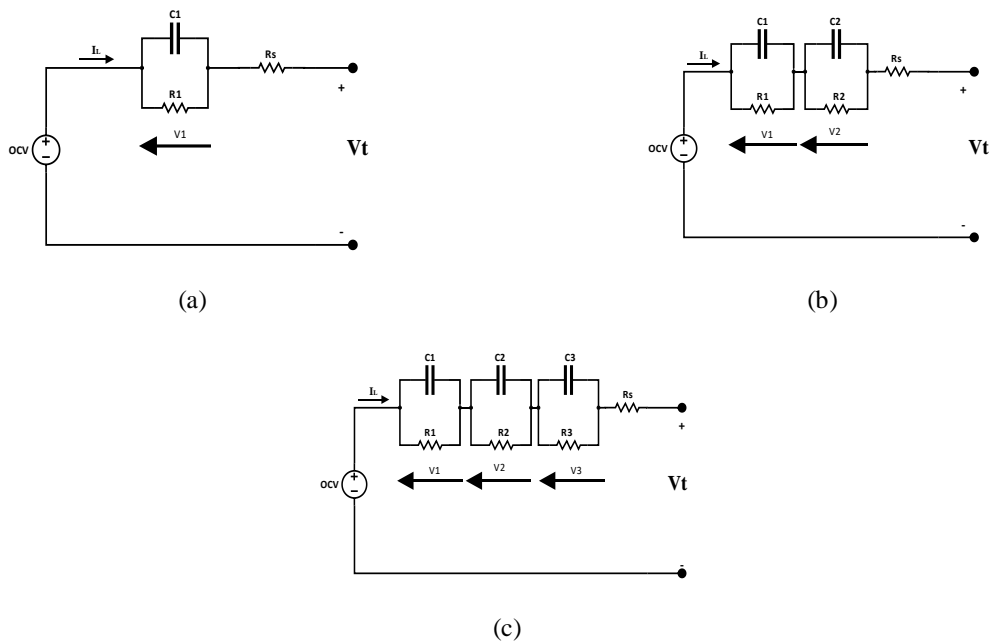


Figure 1. (a) The first order Thevenin model, (b) The second order RC model, (c) The third order RC model

3. PARAMETERS IDENTIFICATION

Before the implementation of the proposed approach to estimating the state, first, the identification of the parameters which the model contains is recommended. In order to determine the parameters of the model a pulse discharge method is applied. A test bench settles in to figure out these factors, a lead-acid battery is carried out in this experiment with a nominal voltage and capacity of 12 V and 22 Ah respectively. The OCV curve can be obtained based on the voltage measurement after the battery reaches its balance voltage. In this paper, the battery is fully charged and has been left a period to get its equilibrium, we measure the OCV at the beginning of the test. Then the cell discharged of 10% capacity with a current of 1C, and let it in a relaxation period. We measure the OCV value with the 0.9 SOC, the steps can be repeated until the battery is fully discharged.

It is clearly appearing that the main objective of this test is to excite the dynamics of the cell for a pulse discharge. The terminal voltage and current curves are illustrated in Figure 2. The terminal voltage

interval from around 12.83 V to 10.5 V when the pulse discharged applied, but it can be observed that returns back to 11 after relaxation.

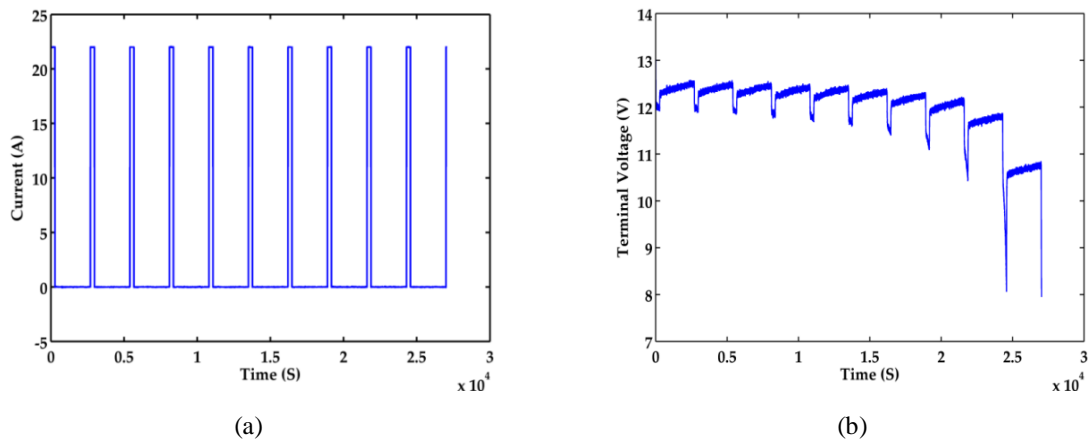


Figure 2. Pulse discharge, (a) Current 1C rate, (b) Terminal voltage measured

3.1. Electrical model parameters

Based on the curve fitting tool in MATLAB, an equation of six-order polynomial built by the measured data is employed to simulate the open circuit voltage, as shown in Figure 3. Before applying the approaches technique for the SOC prediction, the state transition and measurement update equations that link the SOC to the terminal voltage based on the equivalent circuit model necessary to be built firstly. The transient response voltage for a period a pulse discharge is presented in Figure 4(a). The components of the equivalent circuit model can be identified from the transient voltage. The voltage across the branch RC for the loaded in and the relaxation period is written in (4) and (5) as mentioned the Figure 4(b).

$$R_0 = \left(\left| \frac{V_1 - V_2}{I_L} \right| + \left| \frac{V_3 - V_4}{I_L} \right| \right) / 2 \quad (4)$$

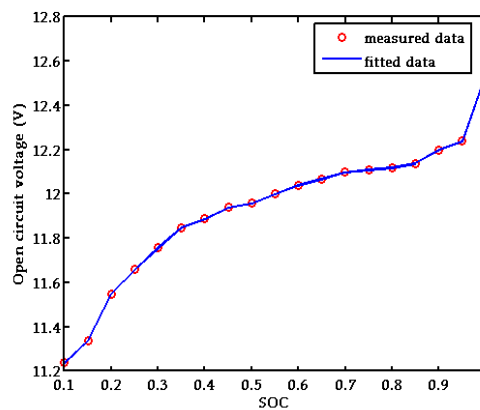


Figure 3. The relationship between open circuit voltage and SOC

The transient parameters can be identified from the present equation for the first model by using LS method [26]:

$$\begin{cases} V_d = I_L * R_p * \left[1 - \exp\left(\frac{-t_d}{\tau}\right) \right] & , I_L \neq 0 \\ V_d = V_d * \left[\exp\left(\frac{-t_r}{\tau}\right) \right] & , I_L = 0 \end{cases} \quad (5)$$

Where, I_L denotes the discharge current, t_d is the time of the discharge period and t_r is the time of the rest period for the model(a) as illustrated in Figure 1(a). And similarly, the transient parameters for the (b) and (c) models can be identified by adding the second branch transient and third transient as illustrate in the Figures 1(b) and Figure 1(c).

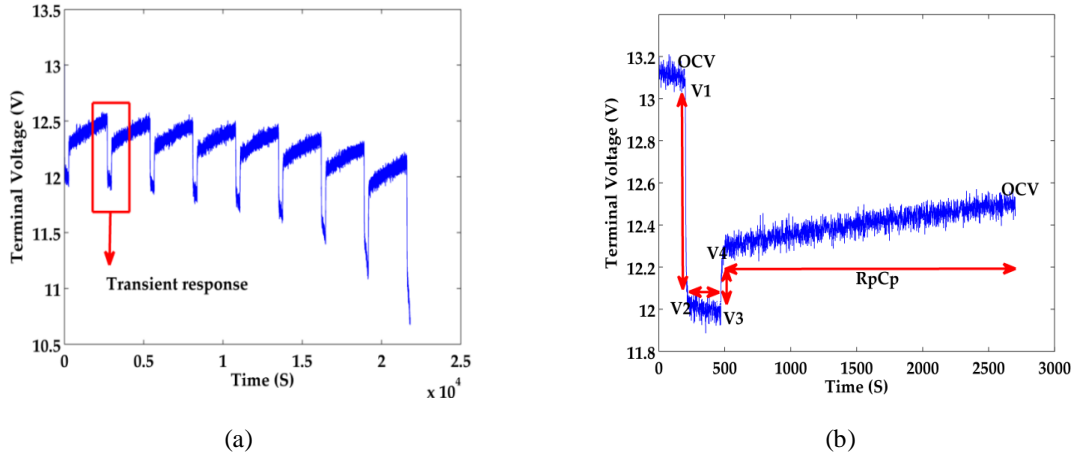


Figure 4. The parameters identification method for Thevenin method, (a) Voltage response, (b) Zoomed transient response

3.2. The state of charge

The SOC is defined in the literature as a ratio refers to the remaining energy in the battery. It indicated in the range of 0 and 1 or expressed in percentage. The SOC function given by:

$$SOC_t = SOC_0 - \frac{1}{C_n} \int_0^t n_i I_{L,\tau} d\tau \tag{6}$$

Where SOC_t is the current time. SOC_0 is the initial value of the SOC, I_L is the current flow in the load assumed negative for charge and positive of discharge. C_n is the present available capacity, which may change by the age effect. n_i refers to the coulomb efficiency. Afterwards, the equation can be transformed to the discrete time form as:

$$SOC_k = SOC_{k-1} - n_i \frac{I_{L,k}\Delta t}{C_n} \tag{7}$$

Where Δt is the sampling time.

3.3. AEKF algorithm

Several models linked to the battery, such as electrochemical models and ECMs have been widely used due to the battery system belongs to the nonlinear systems. The version of Kalman filter which is designed to deal with such kind of systems is the extended Kalman filter [27]. It is a recursive filter based on mathematical equations for estimating the states of a process, designed to minimize the mean squared error. It has been used in many fields as tracking and estimating. The main goal to apply AEKF because it can iteratively regulate the gain automatically based on the update of the weight noise coefficient and adaptively adjusts the output model with the measured voltage. The state space equations of the three models can be formulated and presented as [28-30]:

$$\begin{cases} x_k = A_k x_{k-1} + B_k u_{k-1} + w_k \\ y_k = C_k x_k + D_k u_k + v_k \end{cases} \tag{8}$$

where v_k, w_k are the process and measurement noise with zero mean Gaussian respectively of the nonlinear functions [27, 29] $f(.)$ and $g(.)$. Therefore, based on the equivalent circuit of the three selected batteries models, u_k is selected as the input current and the output of the system y_k is the terminal voltage. x_k is the system states; here are the matrices of the systems as follow in (9) for the three models respectively.

$$\begin{array}{l}
 \text{Model (a)} \\
 \left\{ \begin{array}{l} A_k = \begin{bmatrix} e^{-\frac{T}{R_1 C_1}} & 0 \\ 0 & 1 \end{bmatrix} \\ B_k = \begin{bmatrix} R_p(1 - e^{-\frac{T}{R_1 C_1}}) \\ -\frac{T}{C_n} \end{bmatrix} \\ C_k = \begin{bmatrix} -1 & \frac{\partial OCV}{\partial SOC} \end{bmatrix} \\ D_k = [-R_0] \end{array} \right. \\
 \\
 \text{Model (b)} \\
 \left\{ \begin{array}{l} A_k = \begin{bmatrix} e^{-\frac{T}{R_2 C_2}} & 0 & 0 \\ 0 & e^{-\frac{T}{R_1 C_1}} & 0 \\ 0 & 0 & 1 \end{bmatrix} \\ B_k = \begin{bmatrix} R_2(1 - e^{-\frac{T}{R_2 C_2}}) \\ R_1(1 - e^{-\frac{T}{R_1 C_1}}) \\ \frac{T}{C_n} \end{bmatrix} \\ C_k = \begin{bmatrix} -1 & -1 & \frac{\partial OCV}{\partial SOC} \end{bmatrix} \\ D_k = [-R_0] \end{array} \right. \\
 \\
 \text{Model (c)} \\
 \left\{ \begin{array}{l} A_k = \begin{bmatrix} e^{-\frac{T}{R_3 C_3}} & 0 & 0 & 0 \\ 0 & e^{-\frac{T}{R_2 C_2}} & \frac{T}{C_n} & 0 \\ 0 & 0 & e^{-\frac{T}{R_1 C_1}} & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \\ B_k = \begin{bmatrix} R_3(1 - e^{-\frac{T}{R_3 C_3}}) \\ R_2(1 - e^{-\frac{T}{R_2 C_2}}) \\ R_1(1 - e^{-\frac{T}{R_1 C_1}}) \\ -\frac{T}{C_n} \end{bmatrix} \\ C_k = \begin{bmatrix} -1 & -1 & -1 & \frac{\partial OCV}{\partial SOC} \end{bmatrix} \\ D_k = [-R_0] \end{array} \right. \quad (9)
 \end{array}$$

Where A_k and B_k are discrete system matrix and discrete input matrix for system, respectively T is the sampling time with 1 second, and k is the step. Their covariance values are denoting as Q_k and R_k respectively to the process noise and measurement noise w_k and v_k . C_n is the capacity of the battery supposed to be constant. Minimizing the mean square error is the base of the AEKF algorithm. It is applying the recursive estimation, involved of the initialization, time update and measurement update. The process is illustrated in Figure 5.

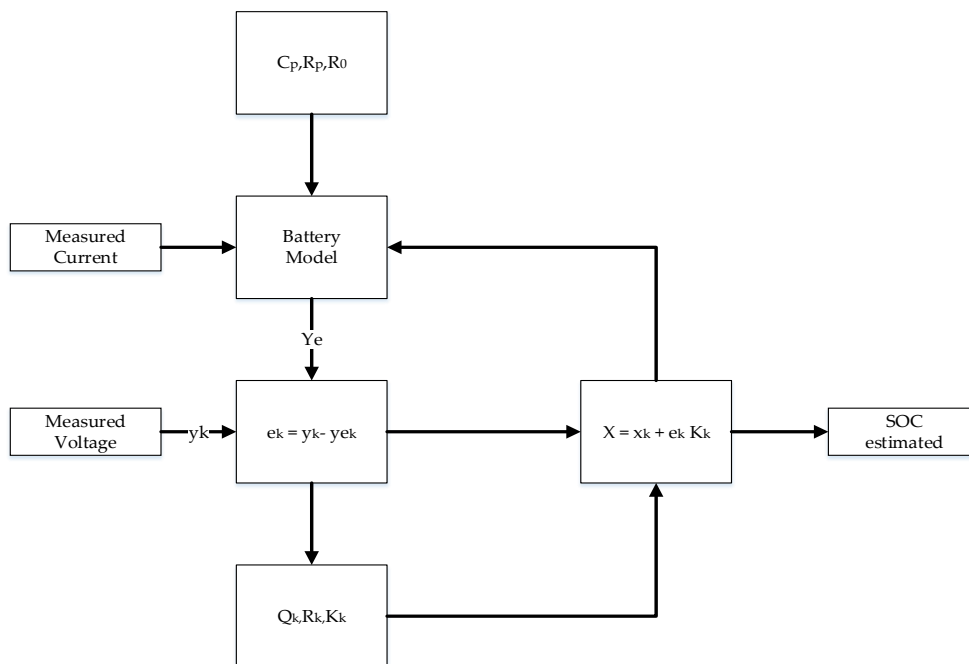


Figure 5. Structure of the process of AEKF

And the steps of the AEKF are summarized as follows:

a. Initialization of parameters:

$$\begin{cases} x_0 = E(x_0) \\ P_0 = var(x_0) \end{cases} \quad (10)$$

Where, E and var are the mean value of state variable and the initial covariance of the system, respectively, The calculation of AEKF consists of six steps.

b. Innovation:

$$e_k = y_k - g(\hat{x}_k^-, u_k) \quad (11)$$

c. Adaptive law:

The covariance has been iteratively updating. Q_k and R_k have been estimated respectively, which cannot estimate accurately in EKF calculation process.

$$H_k = \frac{1}{M} \sum_{k-M+1}^k e_i e_i^T \quad (12)$$

$$R_k = H_k - C_k P_k^- C_k^T \quad (13)$$

H_k is the computation which states covariance of e_k with a moving estimation windows of size M.

d. State estimation covariance and Kalman gain

$$P_k^- = (I + A_k \Delta t) P_{k-1} (I + A_k \Delta t)^T + Q_k \quad (14)$$

$$K_k = P_k^- C_k^T * (C_k P_k^- C_k^T + R_k)^T \quad (15)$$

e. State estimate update

$$\hat{x}_k^+ = \hat{x}_k^- + K_k e_k \quad (16)$$

f. Update state covariance

$$Q_k = K_k^- H_k K_k \quad (17)$$

$$P_k^+ = (I - K_k C_k) P_k^- (I - K_k C_k)^T + K_k R_k K_k^T \quad (18)$$

In the final step, error covariance is estimated and updated. The computing is then repeating again from (b) to (f) until reach all the collected data sampling [30].

4. RESULTS AND SIMULATION

In this practical test, the actual battery's capacity is ranging in the level of 10%-95%, to protect it from damage. The data were used for simulation area, were chosen in order to get the constant discharge curve illustrated in Figure 4. Thus, From Figure 4, it appears that The OCV-SOC relationship drawn is a nonlinear function. In order to investigate the nonlinear behaviour, 4 different functions [17,31] for the OCV proposed to fit the OCV-SOC curve. The functions descriptive are shown in Table 1. Moreover, their parameters were obtained from the curve fitting toolbox in Matlab and evaluated their goodness of fitting.

Table 1. Candidates' functions fitting

Function	Function descriptive
Func1	$OCV = a_1 SOC^6 + a_2 SOC^5 + a_3 SOC^4 + a_4 SOC^3 + a_5 SOC^2 + a_6 SOC + a_7$
Func2	$OCV = a_1 SOC^5 + a_2 SOC^4 + a_3 SOC^3 + a_4 SOC^2 + a_5 SOC^1 + a_6$
Func3	$OCV = a_1 + \frac{a_2}{SOC} + a_3 SOC + a_4 \ln(SOC) + a_5 \ln(1 - SOC)$
Func4	$OCV = a_1 + \frac{a_2}{SOC} + a_3 SOC^2 + a_4 e^{-a_5(1+SOC)}$

The obtained parameters after fitting the curve with each candidate function are shown in Table 2. Followed by the root mean of the sum error (RMSE) for each candidate function, the results are shown in Table 3.

Table 2. Parameters of the selected functions

OCV function	a_1	a_2	a_3	a_4	a_5	a_6	a_7
Func1	142	-439.3	528.7	-308.7	86.69	-8.2	11.45
Func2	24.88	-62.01	60.09	-30.04	9.076	10.54	-
Func3	13.7	0.1009	-2.098	1.428	-0.1778	-	-
Func4	6.406	0.02342	-12.69	0.8754	-1.532	-	-

Table 3. RMSE after fitting

OCVfunction	Func1	Func2	Func3	Func4
RMSE	0.0225	0.0377	0.0203	0.044

The test was settled first to test the performance of the model-based proposed with discharging of the battery under a constant current. The results obtained are shown in Figure 6(a) and Figure 6(b), in comparison with the terminal voltage obtained from the model. Choosing the right OCV function is the key to better estimation the SOC of the battery. Better estimation results were getting when using logarithm, exponential and polynomial functions. The better performance of the higher polynomial function, it is much better than that other OCV functions in the model-based on the first order Thevenin model as shown in Figure 7(a). In Figure 8(a), it can be seen that the SOC error less than the previous shown in Figure7(b). The highest polynomial function fits better than the other functions, and the result become better on tracking by using the second order Thevenin model.

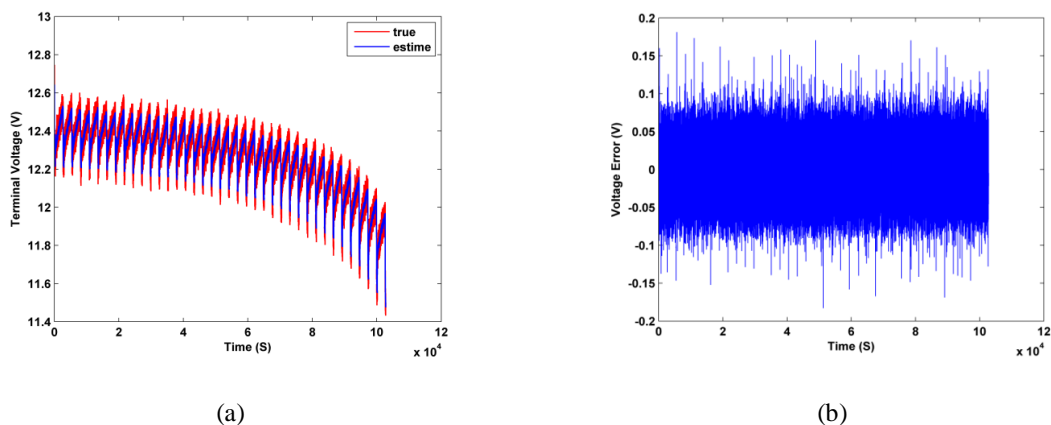


Figure 6. The terminal voltage modelled: (a) the modelling voltage; (b) the modelling error

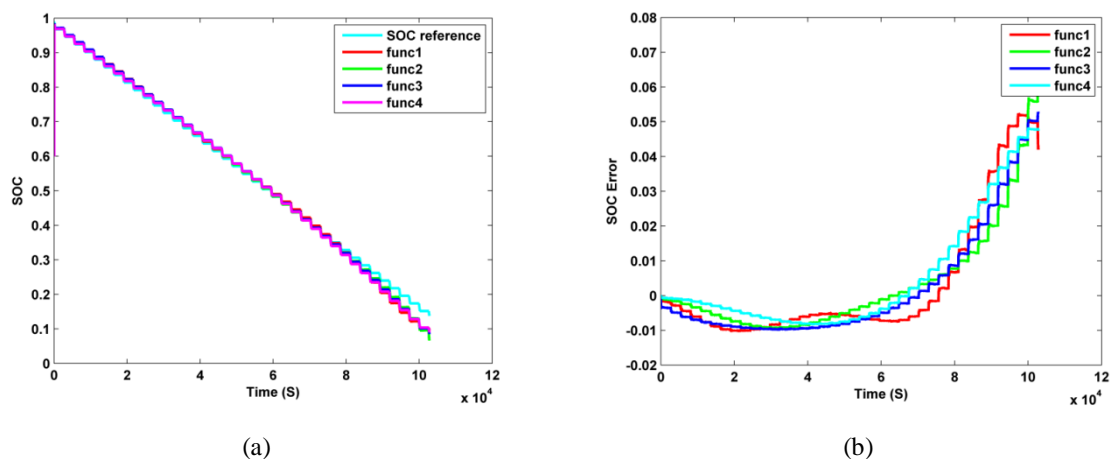


Figure 7. The SOC estimation with initial value of 60%, (a) SOC estimation for first order Thevenin model, (b) The SOC estimation error

In Figure 8(b), it shows the SOC tracking become well than the previous results seen in Figure 8(a) and Figure 7(b). Also the initial SOC given is corrected; thus, it took some period of time to get the correction .in addition, the RMSE for each function with the third ECM model. Although the Kalman filter suffered from the initialization error. However, the EKF perform better with the third order model and the high polynomial function of the OCV even when the model was affected by the noise. The RMSE for the SOC estimated are tabulated in Table 4.

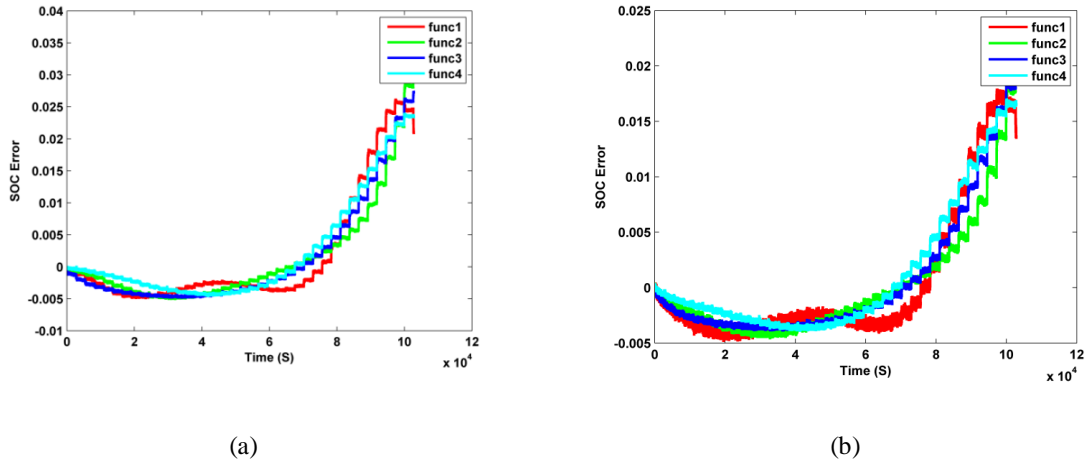


Figure 8. The SOC estimation error, (a) For second-order model, (b) For third-order model

Table 4. The RMSE of SOC estimated for third model-based

Function	Func1	Func2	Func3	Func4
RMSE	0.0144	0.0168	0.0193	0.0201

The state of charge of the battery can be estimated with sliding mode observer (SMO) algorithm. This solution is simple and optimal for estimating the SOC. So, considering the battery system with the sliding variable V_t and the error defined as the sliding surface $e(t) = V_t - \hat{V}_t$, where V_t and \hat{V}_t are the terminal voltage and the terminal voltage estimate. The SMO is modeled as:

$$\begin{cases} \dot{\hat{x}} = f(\hat{x}, u) + k * sgn(y - \hat{y}) \\ \hat{y} = C(\hat{x}) \end{cases} \tag{19}$$

where sgn is signum function. k is the switching gain. y and \hat{y} denote the true terminal voltage and estimated terminal voltage V_t, \hat{V}_t , respectively. u is the input control, which represent the current I_L . \hat{x} is the estimated states. C is the matrix of control.

Therefore, the AEKF has shown better tracking capability to the real SOC against conventional SMO, also has a smooth error during the estimation, which means suitable and robustness technique as shown in Figure 9. Moreover, the RMSE of AEKF equal 0.018 and SMO 0.021, but the SMO is the speed one by computational time under 0.2 S.

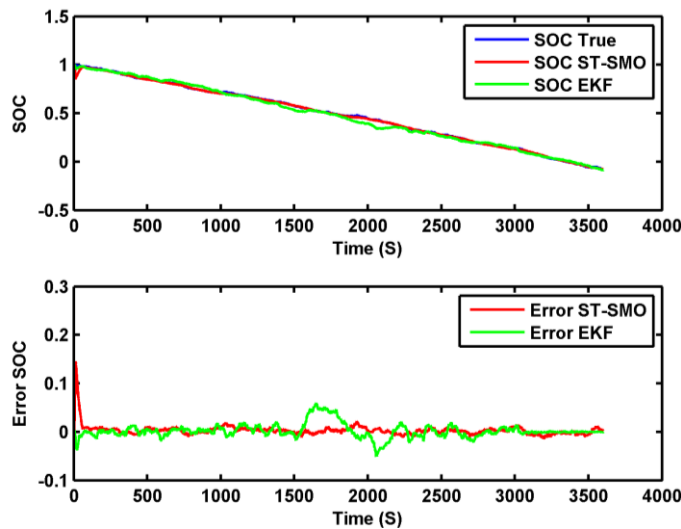


Figure 9. Comparison between AEKF and SMO

5. CONCLUSION

This paper lies in development and testing of an algorithm of SOC estimation for a wide range of operational scenarios. There exists a difficulty in limitation of the performance of the Kalman filtering algorithm because of the nonlinearity in such systems. Thus, It is hard to acquiring suitable battery system data for several profiles. In this paper, an experimental data has been simulated for the model of a Lead-Acid battery to test the algorithm with different drive cycles and compared to simulated ones. The state space model of the battery and its parameters firstly determined and followed by applying the AEKF. The SOC estimation with four different candidate functions was settled. The combination of the EKF with the highest polynomial function and the third order model performed better in limitation of the error. The EKF proved to be more effective and accurate.

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