Parameter Validation to Ascertain Voltage of Li-ion Battery Through Adaptive Control

Bhavani Sankar Malepati, Deepak Vijay, Dipankar Deb and K. Manjunath

Abstract The objective of this paper is to ascertain the open- circuit voltage of a Lithium-ion battery in the presence of an uncertain parameter. The parameter relating to the state of charge (SoC) and open-circuit voltage are considered. An adaptive control law is developed to compensate for the uncertain parameter by considering its possible range of variation and estimating that parameter. Lyapunov stability analysis is carried out to ensure asymptotic stability and signal boundedness of the states associated with the system. The effectiveness of the methodology employed is verified by studying the dynamics of the battery in charging and discharging modes of operation. The robustness of the proposed adaptive controller is validated by considering the change in uncertain parameter to ensure asymptotic tracking.

Keywords State of charge (SoC) · Parameter uncertainty · Adaptive control
Model Reference Adaptive Control (MRAC) · Li-ion battery

1 Introduction

Nowadays, the applications of battery energy storage system are increasing at a rapid rate with its utilization in many aspects such as power bank for mobile phone [7], transportation through electric vehicle [18], energy backup for microgrid [16], etc. The power output of the battery system needs to be controlled as per system requirement. The main challenges associated while dealing with battery energy storage

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D. Deb et al. (eds.), *Innovations in Infrastructure*, Advances in Intelligent Systems and Computing 757, https://doi.org/10.1007/978-981-13-1966-2_3

system is estimation of SoC and determination of battery voltage for a particular charged condition [2, 12, 22]. The terminal voltage of the battery is usually determined by portraying the characteristics between no-load voltage (symbolized as v_{oc}) and SoC [22]. The particular characteristics of a typical Li-ion battery is shown with a polynomial expression [25].

The motivation behind the present work is to accurately define the no-load voltage versus SoC relationship such that the problem of voltage determination is alleviated. Specifically, ascertaining the coefficients of polynomial expression relating no-load voltage and SoC. The problem of uncertainty in the parameter is overcome through adaptive control. Adaptive control is the suitable option for designing the controller to achieve the best possible operation under uncertain and varying system conditions [5]. In general, the design of controller involves maximizing the performance index. However, the conventional control does not have the potential to adapt to system uncertainties and variations. In this aspect, adaptive controllers possess an edge over other techniques. It involves adaptive updation of control parameter in the presence of uncertainity and/or model variances and thereby enabling the system to achieve desired response [21]. Adaptive control can also be employed along with parameter estimation [1]. There exist adaptive techniques such as Model Reference Adaptive Control (MRAC), Inverse Adaptive Control (IAC), etc., in designing the controller [4, 6, 10, 19, 20]. As stated earlier, the considered model of Li-ion battery consists of an uncertain parameter which can be estimated by employing adaptive control. In particular, Model Reference Adaptive Control (MRAC) is employed to estimate the uncertain parameter. Here, the dynamics of the working battery model will be in accordance to the dynamics of the reference battery model.

The rest of the document is organized as follows. Modeling of lithium-ion battery is explained in Sect. 2. Section 3 deals with the adaptive control law developed to meet the objective of parameter validation. Simulation results are verified in Sect. 4. Finally, concluding remarks are drawn in Sect. 5.

2 Modeling of Lithium-Ion Battery

A typical lithium-ion battery can be modeled in many ways [3, 9, 15, 26, 27]. Modeling of battery storage system can be carried out in a simpler manner through equivalent circuit representation [17]. In the present work, equivalent circuit representation is followed up to second order [8] where a dependent voltage source v_{oc} is placed in series with a source resistance R_s and two RC combinations as shown in Fig. 1. Here, the dependent voltage source (i.e., open-circuit voltage of battery v_{oc}) is treated as the function of SoC. The mathematical relation between v_{oc} and SoC is usually shown with a second-order polynomial expression. However, the aforesaid relation is found to be linear in certain region [17]. For simplicity, only linear region is considered in the present work. The open-circuit voltage is expressed as

$$v_{oc} = a_1 x_{\text{soc}} + a_0. \tag{1}$$

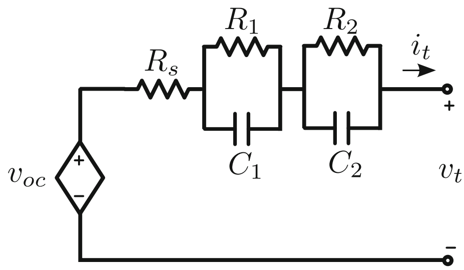

Fig. 1 Equivalent circuit representation of Li-ion battery

In other words, the characteristics between these variables is taken as a straight line with slope as 'a_1' and y-intercept as 'a_0'. The state variables of the considered battery are x_{soc} (SoC), voltage across capacitors C_1 and C_2 (symbolized as v_1 and v_2). The variation of SoC with time is governed by the following expression.

$$x_{\text{soc}}(t) = x_{\text{soc}}(0) - \frac{1}{Q}\int_0^t i_t \mathrm{d}t \tag{2}$$

where, 'Q' and '$x_{\text{soc}}(0)$' refers to rating of the battery in Ampere hour or Coulomb and initial state of charge, respectively.

The state equations of the battery are as follows:

$$\begin{aligned} \dot{x}_{\text{soc}} &= \frac{-1}{Q} i_t \\ \dot{v}_1 &= \frac{-1}{R_1 C_1} v_1 + \frac{1}{C_1} i_t \\ \dot{v}_2 &= \frac{-1}{R_2 C_2} v_2 + \frac{1}{C_2} i_t. \end{aligned}$$

The terminal voltage equation of the battery is shown below.

$$v_t = a_1 x_{\text{soc}} + a_0 - v_1 - v_2 - R_s i_t. \tag{3}$$

The above equation holds good in discharging mode of operation, i.e., battery acting as a source. The same equation in charging mode of operation can be obtained by reversing the direction of terminal current. The particular battery system can be modeled by taking terminal current and voltages as input and output variables, respectively. The described system consists of the uncertain parameters a_0 and a_1 in the output. In this paper, the adaptive control law is developed to address the uncertainty pertaining to a_1, assuming a_0 is a known parameter. The equations can be rearranged by choosing a new state x_1 given by

$$x_1 = a_1 x_{\text{soc}}. \tag{4}$$

In realizing the same system with new variables, the uncertainty can be seen in state x_1 rather than in the output. For simplicity, consider $v_1 = x_2$ and $v_2 = x_3$. For the terminal current of u(t), the state equations are as follows:

$$\begin{aligned}
\dot{x}_1 &= \frac{-a_1}{Q}u(t) \\
\dot{x}_2 &= \frac{-1}{R_1C_1}x_2 + \frac{1}{C_1}u(t) \\
\dot{x}_3 &= \frac{-1}{R_2C_2}x_3 + \frac{1}{C_2}u(t) \\
y(t) &= a_0 + x_1 - x_2 - x_3 - R_s u(t).
\end{aligned} \tag{5}$$

In many applications, each state variable may not be directly measurable [24]. In the working system, SoC of Li-ion battery cannot be measured directly. The other state variables are insignificant in the present context as the physical phenomena of battery is realized in the form of equivalent circuit. Hence, a state estimator like Kalman filter is used with rational assumptions [12, 26]. It is an algorithm which estimates the system states where few (or all) states are not directly measurable. It requires process noise co-variance data along with state-space model of the system [11].

3 Design of the Adaptive Feedback Control Law

A reference system is chosen such that the system has desired characteristics and it is defined as follows:

$$\begin{aligned}
\dot{\hat{x}}_1 &= \frac{-\hat{a}_1}{Q}r(t) \\
\dot{\hat{x}}_2 &= \frac{-1}{R_1C_1}\hat{x}_2 + \frac{1}{C_1}r(t) \\
\dot{\hat{x}}_3 &= \frac{-1}{R_2C_2}\hat{x}_3 + \frac{1}{C_2}r(t) \\
y_r &= a_0 + \hat{x}_1 - \hat{x}_2 - \hat{x}_3 - R_s r(t),
\end{aligned} \tag{6}$$

where $\hat{a}_1$ is the estimated parameter in the reference system, r(t) is the reference signal and the reference states are $\hat{x}_i$, $i = 1, 2, 3$.

Constraint over parameter estimation. The parameter estimate $\hat{a}_1$ is to be updated from an adaptive law and should stay in prespecified regions (that is, $\hat{a}_1 > 0$, since actual parameter a_1 is greater than zero) needed for implementation of the adaptive control. This constraint is built with the understanding that the terminal voltage available is more when SoC is more.

Subtracting (5) from (6) and defining $\tilde{a}_1(t) = \hat{a}_1(t) - a_1(t)$, we obtain the error signals $e_i = \hat{x}_i - x_i$, $i = 1, 2, 3$ as

$$\begin{aligned}
\dot{e}_1 &= \frac{\hat{a}_1}{Q}(u - r) - \frac{\tilde{a}_1}{Q}u \\
\dot{e}_2 &= \frac{-1}{R_1 C_1}e_2 - \frac{1}{C_1}(u - r) \\
\dot{e}_3 &= \frac{-1}{R_2 C_2}e_3 - \frac{1}{C_2}(u - r).
\end{aligned} \tag{7}$$

We define the adaptive update law for the parameter estimate as

$$\dot{\hat{a}}_1 = \frac{p_1}{\gamma Q}e_1 u, \tag{8}$$

and choose adaptive control law $u(t)$ given by

$$u(t) = \big(\frac{-p_1 e_1(t)}{Q}\hat{a}_1(t) + \frac{p_2 e_2(t)}{C_1} + \frac{p_3 e_3(t)}{C_2}\big) + r(t), \tag{9}$$

where p_i, $i = 1, 2, 3$ are the constants which could be adjusted in order to obtain the desired response.

Lemma 1 *The adaptive control scheme with control law u(t) in the (9) updated by the adaptive law in (8), when applied to linear error dynamics (7) ensures that the all closed loop signals within the system are bounded and the tracking error asymptotically approaches zero, that is,* $\lim_{t\to\infty} e_i(t) = 0$, $i = 1, 2, 3$ [13, 14, 23].

Proof We define a positive definite function V as follows :

$$V = \frac{1}{2}\sum_{i=1}^{3} p_i e_i^2 + \frac{1}{2}\gamma_1 \tilde{a}_1^2 \tag{10}$$

where $p_i > 0$, $i = 1, 2, 3$ and $\gamma > 0$, and we ascertain the dynamical system for asymptotic stability. After differentiating V in (10), we get

$$\dot{V} = p_1 e_1 \dot{e}_1 + p_2 e_2 \dot{e}_2 + p_3 e_3 \dot{e}_3 + \gamma_1 \tilde{a}_1 \dot{\tilde{a}}_1 \tag{11}$$

Since $\tilde{a}_1(t) = \hat{a}_1(t) - a_1(t)$, so by differentiating $\tilde{a}_1(t)$, we obtain

$$\dot{\tilde{a}}_1(t) = \dot{\hat{a}}_1(t) - \dot{a}_1(t)$$

where $\dot{a}_1$ vanishes as a_1 is constant term. Now, substituting the values of $\dot{e}_i(t)$ from (7) and $\dot{\tilde{a}}_1$ from above in Eq. (11), we have

$$\dot{V} = \frac{p_1\hat{a}_1}{Q}e_1(u-r) - \frac{p_1\tilde{a}_1}{Q}e_1 u - \frac{p_2}{R_1C_1}e_2^2 + \frac{p_2}{C_1}e_2(r-u) - \frac{p_3}{R_2C_2}e_3^2 + \frac{p_3}{C_2}e_3(r-u) + \gamma_1\tilde{a}_1\dot{\hat{a}}_1. \quad (12)$$

On substituting $\dot{\hat{a}}_1$ from (8), the following expressions can be obtained:

$$\dot{V} = \frac{p_1\hat{a}_1}{Q}e_1(u-r) - \frac{p_2}{R_1C_1}e_2^2 + \frac{p_2}{C_1}e_2(r-u) - \frac{p_3}{R_2C_2}e_3^2 + \frac{p_3}{C_2}e_3(r-u). \quad (13)$$

In the above equation, consider V_1 given by

$$V_1 = -\frac{p_3}{R_2C_2}e_3^2 - \frac{p_2}{R_1C_1}e_2^2. \quad (14)$$

It can be seen that $V_1 \leq 0$, because V_1 carries negative definiteness in itself. Therefore,

$$\dot{V} = V_1 + \frac{p_1\hat{a}_1}{Q}e_1(u-r) - \frac{p_3}{C_2}e_3(u-r) - \frac{p_2}{C_1}e_2(u-r). \quad (15)$$

Substituting the adaptive control law given by (9) in the above equation, we get

$$\dot{V} \leq 0. \quad (16)$$

This implies that, asymptotically, the defined function V will become zero. Hence we conclude $\lim_{t\to\infty} e_i(t) = 0$, $i = 1, 2, 3$. It can be noted that the asymptotic stability is not lost though the constraint described earlier is not imposed in the proof.

4 Case Study

In this section, simulation studies are presented to show the efficacy of the employed methodology. The specifications corresponding to Li-ion battery are shown in Table 1. The gains p_1, p_2 and p_3 are assigned with 5×10^4, 1 and 1 respectively and γ as 10^{-4}. The optimal values of these parameters are selected by changing each of them in an iterative manner from a very low value to very high value. Table 2 shows the nominal values and range of the parameters a_0, a_1 and SoC [15, 17].

Table 1 Main specifications of the Li-ion Battery

Symbol	Description	Value	Units
Q	Capacity of the battery	2.5	Ah
R_s	Series resistance	0.01	Ohms
R_1, R_2	RC branch resistances	0.016	Ohms
C_1, C_2	RC branch capacitances	2200	Farads

Table 2 Nominal and range of parameters for a typical Li-ion battery

Parameter/state	Nominal value	Range
a_0	3	[2.5, 5]
a_1	0.5	[0.05, 0.6]
SoC	0.8	[0.05, 0.95]

In this simulation, the considered Li-ion battery model is subjected to both charging and discharging modes of operation. Initially, battery is charged with a current 1.2 A for 300 s and then discharged with 0.8 A for next subsequent 300 s as shown in Fig. 2. The chosen lower limit for the estimated parameter for a_1 is 0.001. The applicability of adaptive control is verified by introducing a sudden disturbance in the parameter a_1 at 450th sec, which changes from initial 0.5–0.7. Although such a disturbance may be unrealistic, the control technique is designed to trace the particular parameter. It can be seen in Fig. 3 that the change in the actual parameter leads to the change in estimated parameter. The tracking error e_1 is observed to settle at zero as shown in Fig. 4. Figures 5 and 6 shows the Terminal Voltage and the estimated SoC respectively. It is evident that both the quantities tend to increase during charging and decrease while discharging. The rate of change of voltage and SoC becomes negative after 300 s since the current in battery changed its direction. Also, it is noteworthy that there is no major change in the output voltage in the event of disturbance introduced in the parameter a_1 at 450th s. The reason behind this particular observation is due to the appropriate estimation of a_1 by adaptive controller.

It is to be noted that the task of ascertaining terminal voltage is accomplished through proper estimation of uncertain parameter a_1. In other words, the terminal voltage of the battery can be determined by assigning the final estimated value of the parameter in the voltage equation shown in (1).

5 Concluding Remarks

In this paper, an adaptive control technique is presented against the problem of parameter uncertainty associated with Li-ion battery. The task of determining the terminal voltage of the battery is accomplished through validation of uncertain parameter

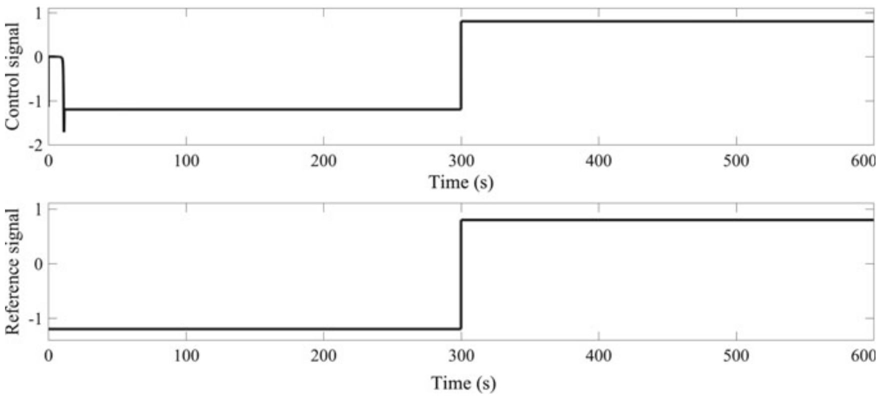

Fig. 2 Top: Control input signal; Bottom: Reference input signal

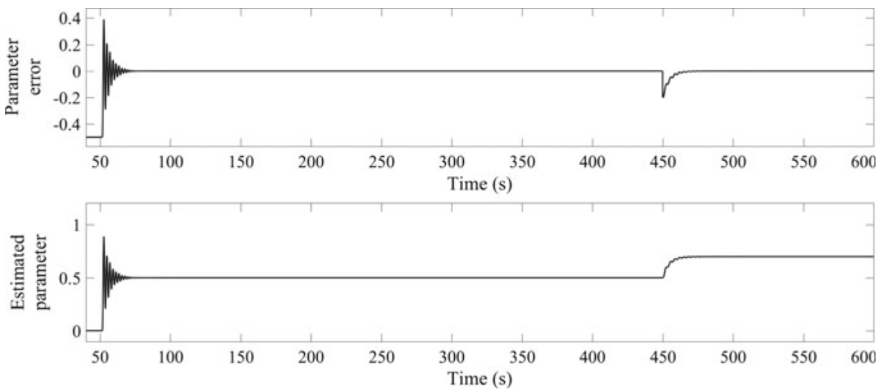

Fig. 3 Top: Parameter error, Bottom: Parameter estimate

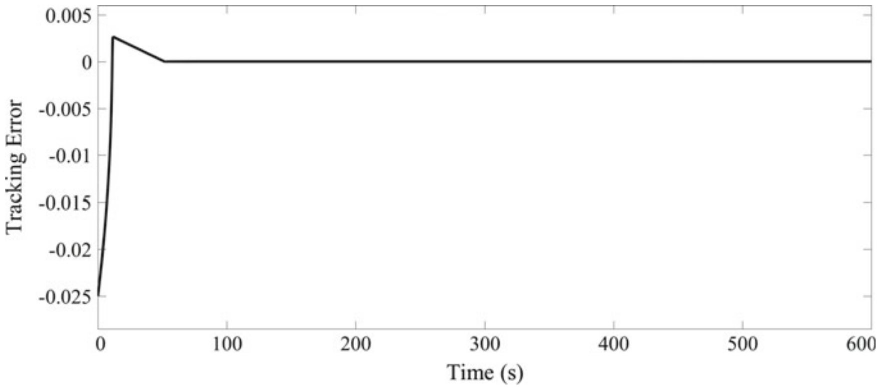

Fig. 4 Tracking error of the state x_1

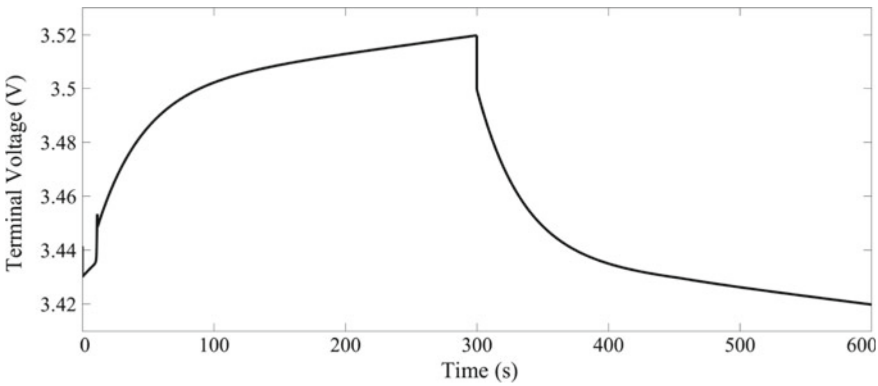

Fig. 5 Terminal voltage of the battery

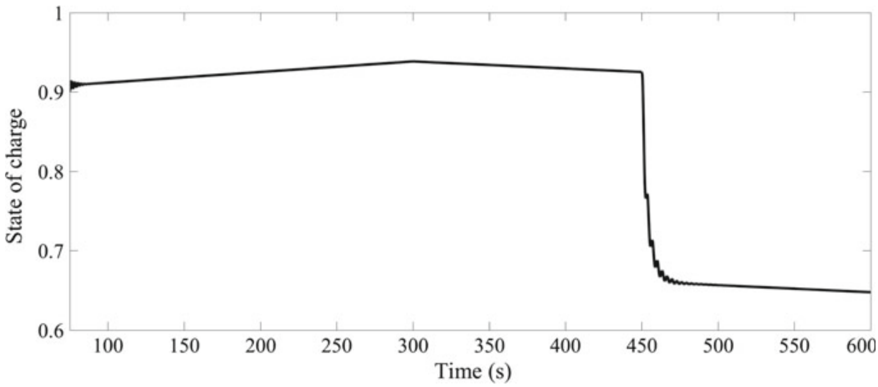

Fig. 6 SoC of the battery

with an assumption that SoC can be estimated. Moreover, the proposed technique is verified even under the variation of uncertain parameter in order to maintain the desired response. The methodology described may find a practical application in the testing and operation of Li-ion batteries.

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