Adaptive Lead–Acid Battery Modelling using RC Method

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Abstract

The lead-acid battery in electric vehicles, constantly subjected to charging and discharging process resulting into depreciation in its performance. In this study, the battery is modeled as an RC circuit using Kalman filter method. Each element in the circuit represents certain battery characteristic. The parameters of the model are computed using parameter estimation techniques and sliding mode control. The results indicate that the proposed technique accurately estimates the battery model parameters with an error of just 0.05% in the most cases. Hence this method can be employed in battery monitoring algorithms for the online estimation of state of charge and predicted time to run for many applications.

1 Introduction

The popularity of Hybrid-Electric Vehicles (HEV) in today's automotive industry is because of its higher fuel efficiency and reduced emissions of polluting gases. Since the battery forms an integral part in the operation of the vehicle it becomes essential to know the available charge left in the battery, how long will it be able to provide required energy, and also about the life of the battery. Researchers around the world developed a wide range of battery models with varying degrees of complexity [1, 2]. These days with the use of lead-acid batteries becoming more critical in HEVs, on-line modeling (adaptive) is becoming significantly important in order to compute the battery parameters, even when the vehicle is in operation, and to keep updating the model to give a more accurate value of the parameters [3, 4, 5]. Adaptive models, however, require few cycles to update the model and give a more accurate model of the battery.

In this study, the lead-acid battery is simulated with Kalman [6] filter method. The estimation parameters consist of two phases. The first phase consists of introducing step change in the input value and the second phase is a time varying input signal.

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2 Battery Model

The adaptive model consists of resistors and capacitors to represent both the steady-state and dynamic characteristics of the battery. Figure 1 shows the circuit diagram for Kalman filter model of battery.

In the above model, R_d represents the self–discharge resistance (which is considered to be quite high and hence can be neglected), capacitor C_b represents the main charge store (i.e. an indicator of the charge of the battery), R_i represents the resistance of the battery terminals and inter–cell connections, while R_t and C_s represent the transient performance of the battery. The voltage across the capacitor C_b is a suitable indicator of the State of Charge (SOC) of the battery while the State of Health (SOH) can be attributed to the change in the value of C_b.

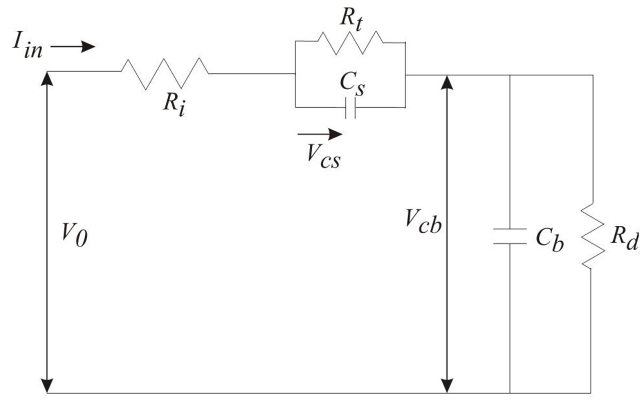


Figure 1: Circuit diagram for Kalman filter model

The differential equations representing the system are given by:

$$\frac{dV_{Cb}}{dt} = \frac{1}{C_b} I_{in} \tag{1}$$

$$\frac{dV_{Cs}}{dt} = -\frac{1}{C_b R_t} V_{Cs} + \frac{1}{C_s} I_{in} \tag{2}$$

The terminal voltage $V_\circ$ can be calculated using the following equation:

$$V_\circ = V_{Cb} + V_{Cs} + I_{in} R_i \tag{3}$$

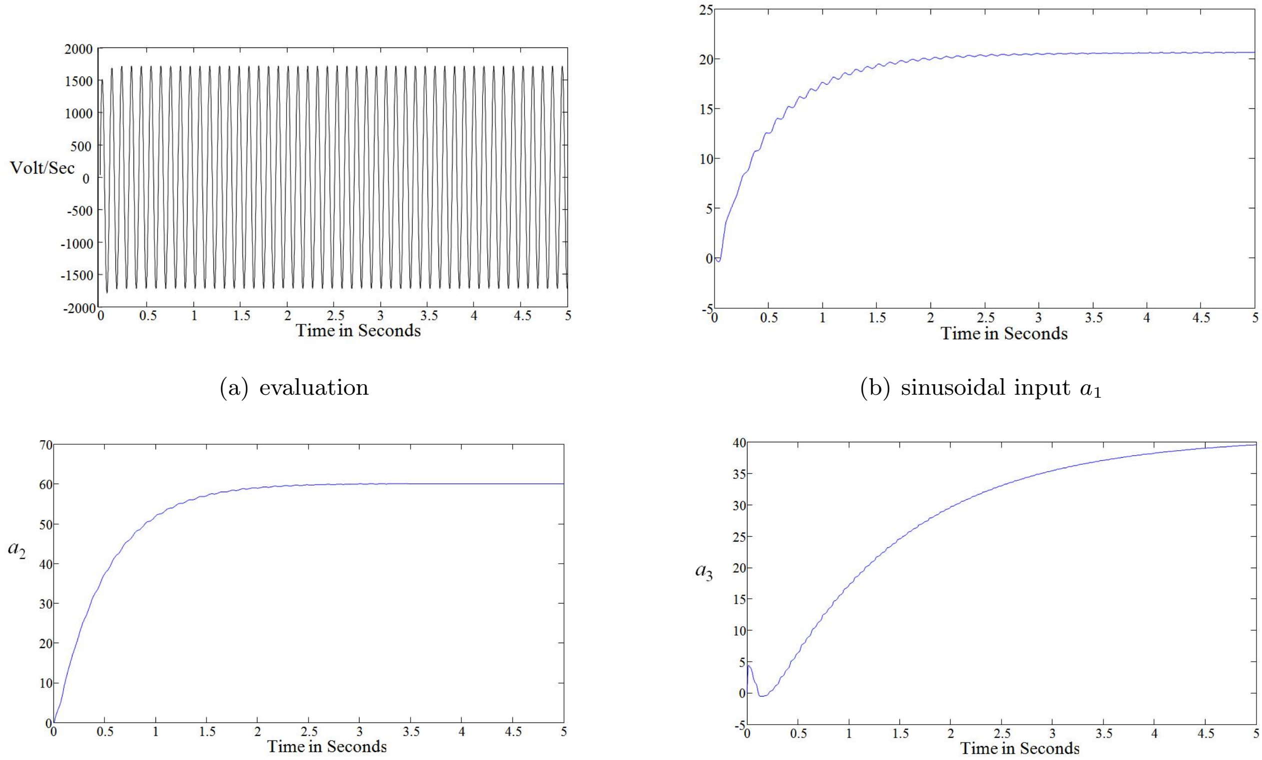
The above equations represent the dynamics of the battery. This relation can be used in the model of the battery to simulate the battery at different loading conditions.

3 Results

The dynamic behavior of the lead-acid battery is studied using the above model. The input current in the first phase is the step function and in the second phase is a time–varying function. In the following, the results for each phase are discussed.

Estimation of R_i

This term represents the internal resistance of the battery. When there is a step change in the input, the values of V_{Cb} and V_{Cs} can not change immediately (since capacitor opposes the changes in voltage). Hence based on Eq. (3), the change in $V_\circ$ is totally attributed to $I_{in} R_i$. From the observed decrease in the output voltage, and from the input step change, the value of R_i can be easily found. To verify our work, the experimental data of ref. [5] is used. By substituting $\Delta V_\circ = 0.48$ V and $I_{in} = 30$ A in Eq. (3) we have $R_i = 16$ mΩ which is the same value of R_i in the Ref. [5].



(a) evaluation

(b) sinusoidal input a_1

(c) sinusoidal input a_2

(d) sinusoidal input a_3

Figure 2: Simulation results

Estimation of C_b

This term represents charge–store capacitor of the battery. The voltage across C_b represents the SOC of the battery. In the present study, not having experimental data, the value of C_b is taken to be constant. Taking the derivative of Eq. (3) with respect to time, one obtains:

$$\frac{dV_\circ}{dt} = \frac{dV_{Cb}}{dt} + \frac{dV_{Cs}}{dt} \tag{4}$$

In Eq. (4), if Δt is large then $V_{Cs} \to 0$ because V_{Cs} is more predominant during short intervals of time and can be neglected when the time interval under consideration is large ($dV_{Cs} \to 0$). Substituting $\frac{dV_\circ}{dt}$ for $\frac{dV_{Cb}}{dt}$ in Eq. (1), the value of C_b can be found. According to the data of ref. [5], $\frac{dV_\circ}{dt} = \frac{\Delta V_\circ}{\Delta t} = \frac{\Delta V_{Cb}}{\Delta t} = 8.943 \times 10^{-5}$ V sec^{-1} and $I_{in} = 30$ mA. Therefore, one can find $C_b = 335427.9$ Farads. The high value of C_b is because the battery stores huge amount of charge.

Estimation of R_t, C_s and V_{Cb}

In Fig. 1, R_t and C_s model the transient behavior of the battery and $V_{Cb}(0)$ represents the initial condition of the voltage across the capacitor C_b. In terms of battery parameters, it represents the initial SOC. Hence, this estimation technique offers the estimation of initial SOC, so that the algorithm does not need to store the values from prior battery cycles. The only drawback in this estimation technique is that the input (I_{in}) should be a time–varying function and can not be constant.

After taking derivative of Eq. (3) using sliding model method [7] one can find:

$$\frac{dV_\circ}{dt} = -\frac{1}{R_tC_s}\left(V_\circ - \frac{1}{C_b}\int_0^t I_{in}dt\right) + \left(\frac{1}{C_s} + \frac{1}{C_b} + \frac{R_i}{R_tC_s}\right)I_{in} - \frac{1}{R_tC_s}V_{Cb}(0) + \frac{1}{R_d}I_{in}\frac{dC_b}{dt} \tag{5}$$

In this work, we assume that C_b is constant, hence $\frac{dC_b}{dt} = 0$. Moreover, I_{in} is chosen as a sinusoidal function i.e. $I_{in} = 30\sin(60t)$. The first simulation is to validate the evaluation of derivative of a function using sliding mode concept. For simplicity, denote $a_1 = \left(\frac{1}{C_s} + \frac{1}{C_b} + \frac{R_i}{R_t C_s}\right)$, $a_2 = \frac{1}{R_t C_s}$ and $a_3 = \frac{1}{R_t C_s} V_{Cb}(0)$. For this simulation the assigned values for the parameters are $a_1 = 60$, $a_2 = 20$ and $a_3 = 40$. That is, we have assumed $V_{Cb}(0) = 2$ V and $R_t = 1193.6\ \Omega$ (These values are truly based on random assumption). Then $\frac{dV_\circ}{dt}$ can be calculated from Eq. (5) shown in Fig. 2(a).

In the next step, the validation of estimation technique is performed. In this simulation, $\frac{dV_\circ}{dt}$ is obtained from the sliding mode method (Eq. 5). Then convergence of the parameters to the actual value is checked. In the simulation, the estimated values are made to pass through a low–pass filter block so as to eliminate the high frequency components in the calculation.

From the results in figures 2(b), 2(c), and 2(d), we see that the asymptotic parameter estimations are $a_1 = 21.023$, $a_2 = 60.0$ and $a_3 = 39.456$. Thus we find that there is an error of around 5% in the values of the estimation. This error is mainly due to 4.5% error in the computation of $\frac{dV_\circ}{dt}$. These estimation are used to compute the value of $R_t = 1194.24\ \Omega$, $C_s = 0.01674$ F and $V_{Cb}(0) = 2$ V giving a respective error of 0.048%, 0.0% and 0.01%. Hence, we see that the errors significantly get reduced in the estimation of R_t and C_s. Consequently, the proposed estimation technique is quite accurate in the estimation of battery parameters such as SOC (related to C_b) for sinusoidal current input.

4 Conclusions

With the rising importance of the lead-acid batteries, both in the automotive industry and the energy sector, it is of critical importance to develop more accurate models of the battery. This paper presents an adaptive model of the battery where the inherent battery parameters are estimated using only the input–output relations of the battery. The proposed estimation technique was employed for the estimation of model parameters. The estimation technique was implemented for sinusoidal current input. From the estimation results, the proposed technique accurately estimates the battery model parameters with an error of just 0.05of the cases. Hence this method can be employed in battery monitoring algorithms for the online estimation of state of charge and predicted time to run for many applications.

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