Adaptive Parameter Identification of Battery Pack in Electric Vehicles with Real-Driving Signals

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Abstract

This paper presents an adaptive identification method for battery parameters in automotive applications such as electric vehicles (EVs). A simple yet accurate electrical equivalent model (ECM) with varying parameters is used to represent the whole battery pack. The modeling process requires the current, voltage, and SOC signals of the battery. Detailed physical knowledge of the battery pack and inside cells are not necessary. The ECM parameter identification approach is developed by employing the NLMS (normalized least mean square) algorithm, which is an advanced adaptive algorithm having fast convergence rate and easier to be implemented. This approach is verified on a 51.2 V, 95AH LiFePO4 battery pack operated in three-wheeler electric bikes. Battery signals during vehicle daily real-world driving were collected over a period of time and used for the ECM parameter identification. The identified internal resistance R_0, R_1 and capacitance C_1 changes obviously over the period of time and the battery degradation is well reflected through the identified parameters of the ECM.

Keywords: adaptive parameter identification, battery modules, battery packs, EV batteries, battery modeling, battery internal resistance/capacitance

1. Introduction

Lithium-ion battery is advantageous over other battery chemistries due to its superiority in capacity density and cycle life, which makes it be dominantly applied as storage devices for electrical vehicles (EVs) [1-3]. However, its performance including capacity and power output will continuously deteriorate with its life cycle due to irreversible physical and chemical changes. The capacity will gradually influence the remainder driving range, whereas the output power will affect the dynamic performance of the EVs. Thus, the accurate estimation of the battery states such as state of capacity (SOC) and state of health (SOH) is needed to maintain battery performance, safety and long life-cycle for the EVs' efficient and safe operation, while the accurate estimation of the states are dependent on the battery model parameter estimation in battery management system.

ECM (equivalent circuit model) is a commonly used model type to represent battery and reproduce its dynamic behavior and voltage response in time domain. In the ECM model, parameters including resistance and capacitance need to be identified to match the real signal of battery. A frequency used identification method for the parameters is offline analytical technique based on HPPC (Hybrid Pulse Power Characterization) test [4-5]. As a real-time parameter estimation method, the recursive least square (RLS) algorithm-based method is widely used, studied in detail in [7-9], and recommended in

[10] after comparison with other methods. In addition, optimization algorithms such as genetic algorithm [11] and Big-Bang Big-Crunch algorithm [12] are applied in battery model parameter identification. Particularly, in [12], vehicle operating signals are used to run the algorithm to identify the battery model parameters.

However, the model parameters are subject to uncertainty due to the battery pack to pack variation, both inherent initial variation and variation caused by different working conditions of different EVs. Therefore, adaptive identification is needed to account for the parameter uncertainties. Furthermore, the parameters, especially the resistance, are important indicator linked to battery health, as they are closely related to battery SOH [13-15]. Thereby, through the parameter adaptive identification over a long period of battery usage time, battery degradation can be evaluated by using the estimated parameter such as internal resistance.

Adaptive parameter identification algorithm can identify the parameter uncertainty and the time-varying modes online, and provide parameter estimation in real-time. Thereby, for the battery parameter estimation using the battery signals of vehicles collected during real-world driving time, we propose to use the adaptive parameter identification algorithm to estimate battery resistance in real time. The NLMS (normalized least mean square) adaptive algorithm [6] is used and easily implemented in Matlab/Simulink. Compared to RLS method, the NLMS method is a simple yet practical method, which has a fast convergence rate and is easier for real-time implementation.

In this paper, the parameter identification for the battery ECM model is conducted for a 51.2 V, 95Ah lithium-ion battery pack installed on three-wheeler electric bikes. The model parameter identification uses the real-time current, voltage and SOC signals of the battery operating in real-world driving of the vehicles. The ECM modeling performance is investigated and verified by comparing the battery voltage signal from the model with the real voltage signal. The identified ECM parameters over the period of time are used to evaluate the battery degradation.

2. Battery ECM model

ECM model is commonly used to reproduce the battery voltage response to a current in a time duration. Fig. 1 shows a well-known structure of battery ECM [16-17]. The structure reproduces the dynamic behavior and the voltage response of a battery which includes transient responses in time durations. In this model, OCV is the open circuit voltage, U is the battery terminal voltage, I is the current, R_0 is the ohmic resistance of the connectors, electrodes and electrolyte, and the parallel RC elements, (R_1, C_1) to (R_n, C_n) connected in series are responsible for transient dynamics.

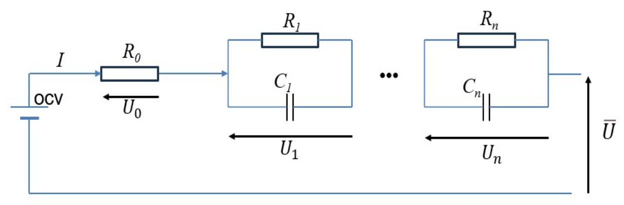


Fig. 1. Battery ECM model structure.

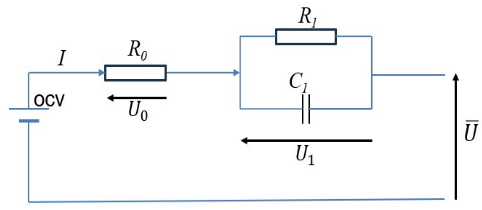


Fig. 2. The first order ECM model.

The equation governing the battery output voltage during discharge is given by

$$\bar{U}(k) = OCV(k) - U_0(k) - U_1(k) - \cdots - U_n(k)\,, \tag{1}$$

where OCV is the open circuit voltage, $U_0(k) = R_0 I(k)$, and each RC circuit has the differential equation as follows.

$$\frac{dU_i}{dt} = \frac{1}{C_i} I - \frac{1}{R_i C_i} U_i, \quad i = 1, 2, \ldots, n, \tag{2}$$

which leads to the discretized equation given by

$$U_i(k) = U_i(k-1) e^{\frac{-\Delta t}{R_i C_i}} + R_i \left(1 - e^{\frac{-\Delta t}{R_i C_i}}\right) I(k)\,, \tag{3}$$

where $\Delta t = t(k) - t(k-1)$ is the sampling time. The transfer function of (3) is written as

$$\frac{U_i}{I} = \frac{R_i (1 - E_i) z^{-1}}{1 - E_i z^{-1}}\,, \quad E_i = e^{\frac{-\Delta t}{R_i C_i}} \tag{4}$$

The overall transfer function is therefore given by

$$\frac{U}{I} = R_0 + \frac{R_1 (1 - E_1) z^{-1}}{1 - E_1 z^{-1}} + \cdots + \frac{R_n (1 - E_n) z^{-1}}{1 - E_n z^{-1}}\,, \tag{5}$$

where U is the difference between $\bar{U}$ and OCV.

The general form of (5) can be written as

$$\frac{U}{I} = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2} \ldots + b_m z^{-m}}{1 + a_1 z^{-1} + a_2 z^{-2} \ldots + a_n z^{-n}}\,, \quad \text{or} \tag{6}$$

$$U(k) = -a_1 U(k-1) - a_2 U(k-2) - \cdots - a_n U(k-n) + b_0 I(k) + b_1 I(k-1) + b_2 I(k-2) + \cdots + b_m I(k-m). \tag{7}$$

This paper focuses on the relationship of the identified parameters with the degradation of the battery by using the proposed adaptive algorithm based on the vehicle real-driving data. For simplicity, the first order ECM [17], as shown in Fig. 2, is thus considered. As such, we have

$$\frac{U}{I} = R_0 + \frac{R_1(1-E_1)z^{-1}}{1-E_1 z^{-1}} \quad . \tag{8}$$

It is easily to derive that in (7),

$$b_0 = R_0, a_1 = -E_1, b_1 = R_1(1-E_1),\ n=1, m=1. \tag{9}$$

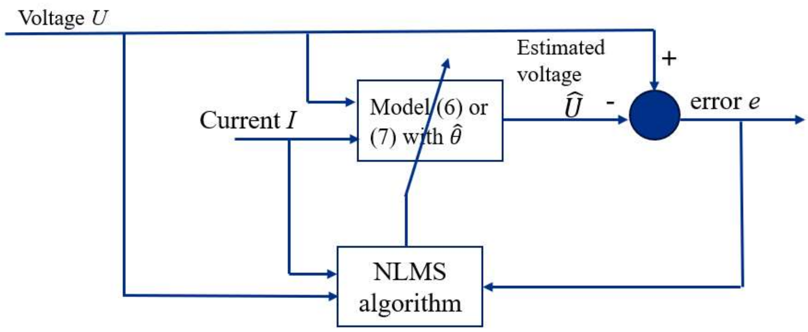


Fig. 3. Block diagram illustrating adaptive parameter estimation algorithm.

3. NLMS adaptive algorithm for ECM parameter identification

Let the parameters in (7) be written as $\theta = [b_0,\ \ b_1 \ldots,\ \ b_m,\ \ a_1,\ \ \ldots,\ \ a_n]^T$, and its estimate is denoted by $\hat{\theta} = [\hat{b}_0,\ \ \hat{b}_1 \ldots,\ \ \hat{b}_m,\ \ \hat{a}_1,\ \ \ldots,\ \ \hat{a}_n]^T$.

Fig. 3 shows the schematic of adaptive parameter identification, where NLMS algorithm is adopted. NLMS algorithm is simpler than RLS algorithm. Thus, it is easier to be implemented, with a fast convergence time and a good accuracy [6]. According to NLMS algorithm,

$$\hat{\theta}(k) = \hat{\theta}(k-1) + \frac{\Gamma\psi(k)e(k)}{1+\psi^T(k)\psi(k)}, e(k) = U(k) - \hat{U}(k), \tag{10}$$

$$\hat{U}(k) = \hat{\theta}^T(k)\psi(k), \psi(k) = [I(k),\ \ \cdots,\ \ I(k-m),\ \ U(k-1),\ \ \ldots,\ \ U(k-n)]^T. \tag{11}$$

Given by the current I and the terminal voltage U, the parameter estimate $\hat{\theta}(k)$ can be obtained by using (10)-(11). Afterwards, the resistance R_i and capacitance C_i can be calculated by solving (9). The algorithm (10)-(11) can be implemented in Simulink/Matlab. Battery current and voltage signals in real-time are injected to the Simulink model, which is run over the time duration of the signals. By running the Simulink model, the estimated parameter vector $\hat{\theta}(k)$ can be obtained.

4. EV battery ECM parameter identification: results and discussion

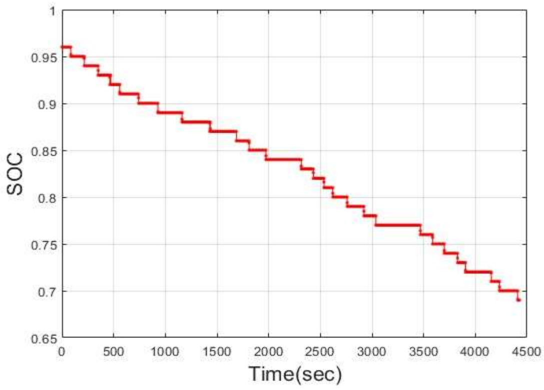
The battery pack is Lithium iron phosphate battery pack, i.e., LiFePO4 battery. The battery pack is installed in electric three-wheeler bikes. The battery pack includes sixteen prismatic battery cells connected in series. The rated capacity is 95AH and nominal voltage is 51.2 V. Each battery cell has a rated capacity of 95 Ah and a nominal voltage of 3.2 V. The proposed ECM parameter estimation approach requires battery current, voltage and SOC signals in real time. The battery signals were collected in real-driving mode for 156 days. The sampling time is 1 sec. As an example, Fig. 4 shows the SOC, current, and voltage of the battery in the vehicle in one day, respectively.

To run the algorithm, the battery cell OCV is calculated by using the polynomial function (5) in [18], which applies to LiFePO4 battery. The OCV of the battery pack used in the vehicle is the cell OCV multiplied by 16 as the battery pack is composed of 16 cells in series connection. Because the OCV is calculated from the collected SOC real-time signal, SOC needs to be accurate, which can be ensured since it is available from BMS.

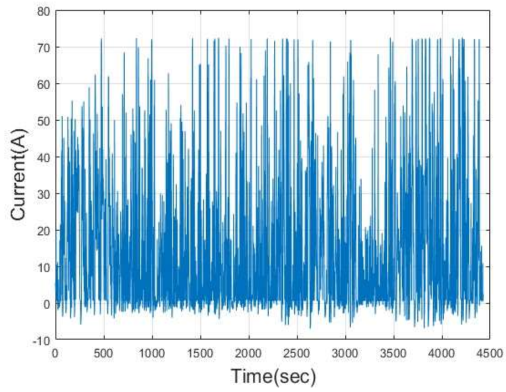
The battery signals of current, voltage and SOC during each driving were injected to the NLMS algorithm implemented in Matlab/Simulink. By running the Simulink model, $\widehat{U}(k)$ and $\hat{\theta}(k)$ were available. As an example, an estimated voltage, i.e., $\widehat{U}(k)$, is shown in Fig. 4c and compared with the real voltage signal. The error between the estimated and the real voltage is shown in Fig. 4d. The mean square error (MSE) of the error is 0.0057, which is less than 1% of the voltage peak-to-peak value. This means that the ECM model well reproduces the voltage response of the battery to the given current.

The estimated parameter $\hat{\theta}(k)$ were used to calculate the parameters R_0, R_1, C_1 by solving (9). As a result, the estimated $R_0(k)$ time-sequence is shown in Fig. 5, on several dates selected to show the difference of $R_0(k)$ The final value of each $R_0(k)$ time-sequence is taken as the internal resistance value on each date or cycle. The obtained internal resistance in each cycle is shown in Fig. 6, where it increases due to the battery degradation. It is known that battery internal resistance will increase with battery degradation [19-21], which means that the obtained internal resistance plotted in Fig. 6 agrees with the results in literature. Similarly, the internal resistance R_1 and the capacitance C_1, were also obtained and plotted in Figs. 7 and 8, respectively. It is observed that R_1 increases and C_1 decreases with battery degradation. This is easily understood as battery capacity becomes lower with degradation which affects the amount of available charge in the battery, and the RC pair represents the charge-transfer phenomenon inside the battery [8].

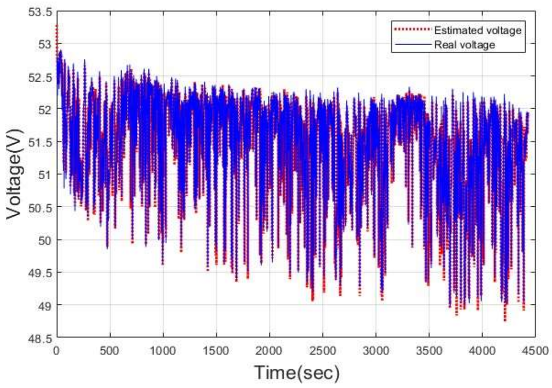
To this end, it is seen that the proposed NLMS algorithm-based approach has accomplished real-time estimates of the EV battery internal resistance and capacitance, given by battery voltage, current and SOC signals during the vehicle real-driving. The battery degradation can therefore be evaluated by investigating the change of the battery parameters which are estimated by applying the proposed approach for every time of driving.



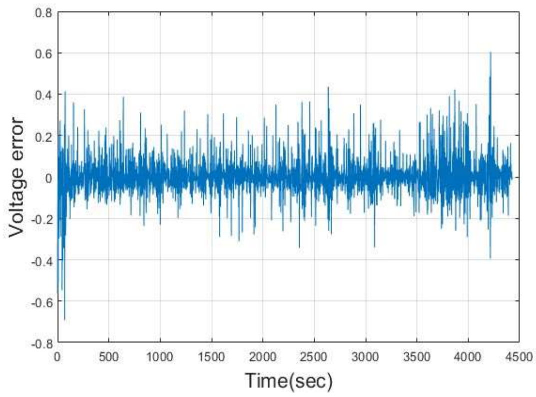
a. SOC of the battery in one day.



b. Current of the battery.



c. Voltage comparison.



d. Voltage error (MSE=0.0057).

Fig. 4. Signals of the battery in the vehicle in one day.

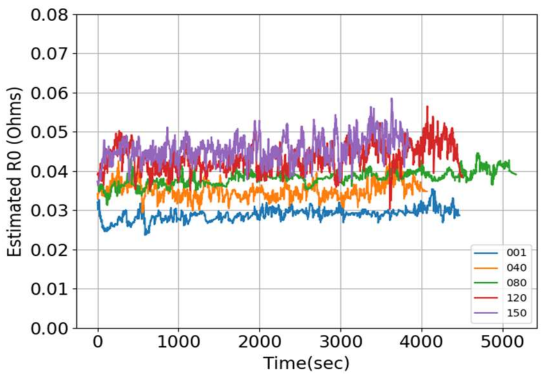


Fig. 5. Estimated real-time R_0 of the battery with the signals collected in the selected days.

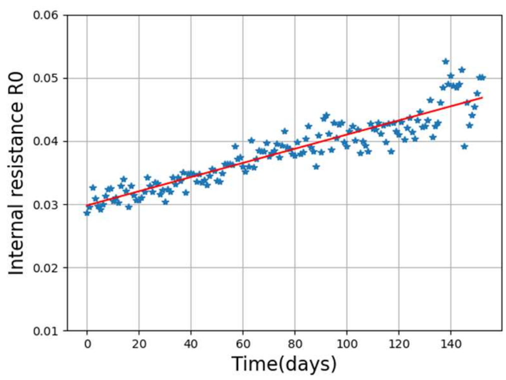


Fig. 6. Battery parameter degradation: R_0 versus the battery usage time.

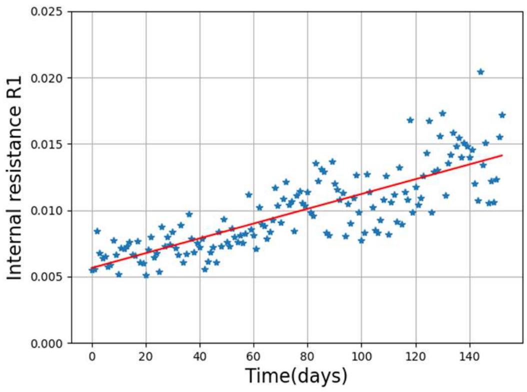


Fig. 7. Battery parameter degradation: Internal resistance R_1 versus the battery usage time.

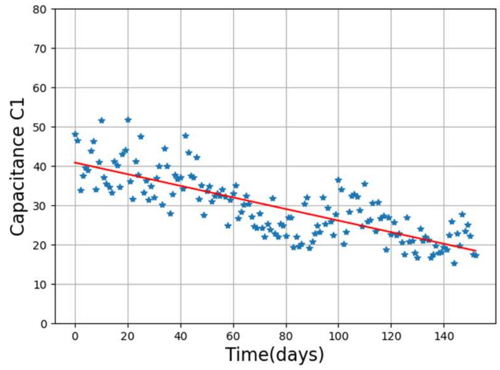


Fig. 8. Battery parameter degradation: Capacitance C_1 versus the battery usage time.

5. Conclusion

In the paper, the ECM parameter identification of the battery used in the electric vehicles have been studied. The parameters are internal resistances R_0, R_1 and capacitance C_1. The battery current, voltage and SOC signals collected when the vehicle is in real-world driving have been used to identify these battery parameters. The adaptive algorithm NLMS has been utilized in the proposed approach, which has been implemented with these real-time signals. With the identified parameters, the ECM has well reproduced the voltage response to the current, and the identified ECM parameters have clearly reflected the degradation of the battery over the usage time. As such, the proposed approach can be applied to evaluate the battery degradation with the real-time signals through the parameter identification. The proposed ECM parameter identification approach uses real-time signals of current, voltage and SOC, thus applicable to the practical situations with temperature effect and other battery chemistries.

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