리튬인산철 배터리를 위한 새로운 히스테리시스 모델링

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A novel OCV Hysteresis Modeling for SOC estimation of Lithium Iron Phosphate battery

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ABSTRACT

The relationship of widely used Open circuit Voltage (OCV) versus State of Charge (SOC) is critical for any reliable SOC estimation technique. However, the hysteresis existing in all type of battery which has been come to the market leads this relationship to a complicated one, especially in Lithium Iron Phosphate (LiFePO4) battery. An accurate model for hysteresis phenomenon is essential for a reliable SOC identification. This paper aims to investigate and propose a method for hysteresis modeling. The SOC estimation is done by using Extended Kalman Filter (EKF), the parameter of the battery is modeled by Auto Regressive Exogenous (ARX) and estimated by using Recursive Least Square (RLS) filter to tract each element of the parameter of the model.

1. Introduction

Due to potentially low cost, high performance in term of higher power density as compared to other types of battery, $LiFePO_4$ batteries have a significant growth in use of energy storage systems of the plug-in hybrid electric vehicle (PHEVs), hybrid electric vehicle (HEVs) and electric vehicle (EVs). However, $LiFePO_4$ batteries also produce hysteresis as a special OCV characteristic, the cell OCV during charge is different from OCV during discharge at the same SOC. In addition, a flat OCV in range from 20% SOC to 80% SOC complicates and gives significant influence on SOC estimation accuracy. This hysteresis phenomenon needs to be considered for an accurate battery modeling. Obtaining an effective model will strengthen the SOC estimation instead ignoring or using weak model will give less accuracy or even diverge the estimation error. In this paper, firstly presents discontinuous current test for 10000 mAh battery to gain the SOC-OCV relation as well as determine the hysteresis behavior of this type of battery. Secondly, following the idea of major loop and minor loops, the hysteresis model was developed based on minor loops as detailed as possible to strengthen the accuracy. Finally, the battery is undergoing tests and the actual SOC of the battery is estimated by the combination of the Recursive Least Square (RLS) for parameter identification and EKF considering the hysteresis phenomenon which is mostly focused on.

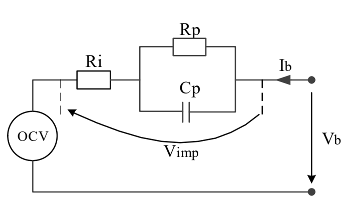

Figure 1. Equivalent circuit model of LiFePO4 battery

2. Battery modeling

Equivalent circuit model (ECM) consists of a resistor and parallel R-C networks connected in series is commonly selected model. It can be identify that two R-C networks is reasonable for battery dynamic modeling including the voltage relaxation voltage of the LiFePO4 which cannot be ignored. A reduced computation cost model using one R-C network by merging the second R-C network into equilibrium voltage reconstructing to a dynamic OCV [1]. The ECM model now is represented as Fig. 1 in which R_i is the pure Ohmic resistance, R_p is the charge transfer resistance, the time constant τ_{RC} of the R-C circuit divided by the charge transfer resistance result in the double layer capacitance C_p.

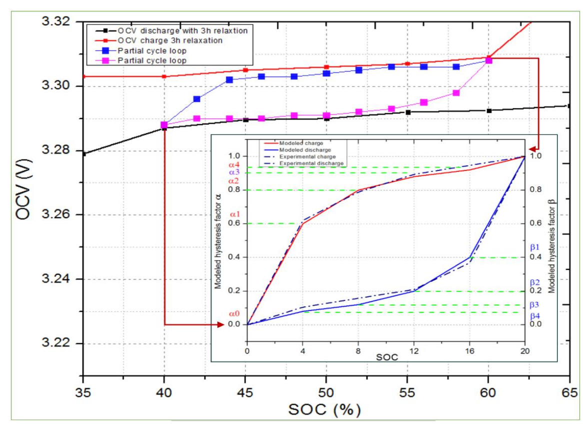

Figure 2. Modeling of a hysteresis loop with a partial cycle test result

Some partial cycles are applied to obtain OCV curves between 2 boundary OCV curves. At first, the fully charged cell is continuously discharged to starting point of SOC (20% SOC) and partially charged to 40% SOC by using 10 current pulses with 2% ΔSOC, after that the cell is discharged with the same current pulses. After each pulse, the cell is leaved for 3h resting to achieve the steady state of the OCV as similar to the SOC-OCV test previously. Then, the test is repeated 3 times at different starting point and range of SOC (40% to 60%, 70% to 90%, 30% to 60%) to verify the behavior. A method is developed to reconstruct the OCV transition which is caused by hysteresis effect. This method introduces α and β as 2 hysteresis factor and Δ as stepping SOC in Fig 2. Fig 2 shows how the method work based on α, β and Δ. ΔSOC increases from 0 to Δ_n when the battery is charged, in the opposite side, ΔSOC decreases from Δ_n to 0 when the battery is discharged. The variation of the OCV between upper boundary curve and lower boundary curve equivalent to α, β which represent for charge and discharge, respectively. Each Δ divides α, β into small parts equally, the more divided the more accuracy achieved but more computation cost, here we use $n=5$, thus each step increasing of n is 4% SOC. α represents for charge, increases from $\alpha_0=0$ to $\alpha_n=1$ when charging ($\alpha_n=1$ if the actual OCV lies in OCV charge) and β represents for discharge, decreases from $\beta_n=1$ to $\beta_0=0$ when discharging ($\beta_n=0$ if the actual OCV lies in OCV discharge) respecting to dimension n ($\alpha_0 \ldots \alpha_n$ and $\beta_0 \ldots \beta_n$). The equation of the factors corresponds to the charge throughput, so that it can be expressed as follow:

$$OCV(SOC,\alpha) = \alpha.OCV_{chr} + (1-\alpha).OCV_{dis}; \quad (4)$$

$$OCV(SOC,\beta) = \beta.OCV_{chr} + (1-\beta).OCV_{dis}; \quad (5)$$

Where, the OCV is a function of SOC and α respecting to the modeled charge region and β respecting to the modeled discharge region. The values of α and β are limited in range of 0 to 1 and obtained by current integration.

3. Online parameters estimation algorithm

As shown in Fig. 1, the parameter of the battery need to be tracked first so that an auto regressive exogenous (ARX) model is required. The transfer function G(s) of the battery impedance is obtained and expressed in s-domain as follows:

$$G(s) = \frac{V_b(s) - OCV(s)}{I_b(s)} = \frac{V_{imp}(s)}{I_b(s)} = R_i + \frac{R_p}{1 + s.R_p.C_p} \quad (6)$$

By using Euler's forward transformation method to convert this transfer function into discrete-time domain, we have:

$$G(z^{-1}) = \frac{a_1 + a_2\, z^{-1}}{1 + a_3.z^{-1}} \quad (7)$$

and the impedance voltage in discrete form is:

$$V_{imp,k} = a_1.I_{b,k} + a_2.I_{b,k-1} + a_3.V_{imp,k-1} \quad (8)$$

Where $a_1 = R_i;\ a_2 = \frac{T}{C_p}\left(1 + \frac{R_i}{R_p}\right);\ a_3 = \frac{T}{R_p.C_p} - 1;$ (9)

Furthermore, to identify these parameters, impedance voltage V_{imp} should be written in a form as:

$$V_{imp,k} = OCV_k - V_{b\,k} = \theta_k.\psi_k \quad (10)$$

With $\theta_k = \left[a_{1,k},\ a_{2,k},\ a_{3,k}\right];\ \psi_k = \left[I_{b,k};\ I_{k-1};\ V_{imp,k-1}\right]$ (11)

Where, ψ_k is the input vector obtained from measured input value including the impedance voltage which is dropped on the battery impedance at previous time index, $I_{b,k}$ and $I_{b,k-1}$ is the measured battery voltage at current time index and previous time index; respectively. To identify the parameter of the model, a wide used method RLS filter is introduced, which reduces computational cost significantly, making the RLS extremely attractive for online parameter identification. For a detailed algorithm, refer to [2], the RLS can be found in many test books and papers.

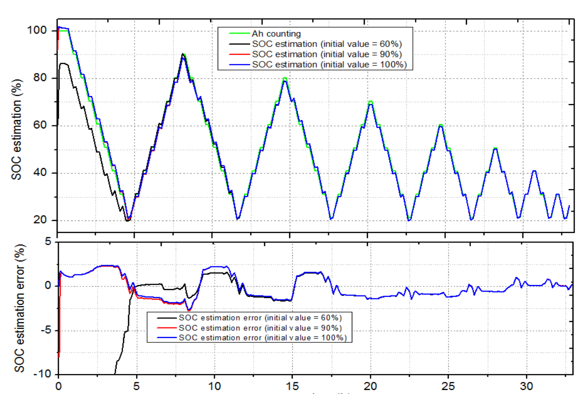

Figure 3. SOC estimation result with different initial values

4. SOC estimation by RLS-EKF combination

The definition of the SOC commonly formulated through current integration, the discrete time form of the SOC can be represented as:

$$SOC_k = SOC_{k-1} + \eta_b.I_{b,k-1}.\Delta t / C_n \quad (12)$$

The reconstructed OCV at each time index k based on Equations (10) is: Where SOC_k and SOC_{k-1} are the SOC at time index k and $k-1$. $I_{b,k-1}$ is the working current and Δt is the sampling time period. EKF is a method for system state estimation in real-time, the algorithm compares measured cell terminal voltage with estimated voltage predicted by the filter through a cell model. The difference between these two values leads to an adaption of state of the cell model. The discrete-time state equations for a non-linear system can be given as:

$$x_k = f(x_{k-1}, u_k) + w_k\ ;\ y_k = h(x_k, u_k) + v_k \quad (13)$$

Where x_k represents the state parameters, f and h are non-linear system function, u_k is the input, w_k is the process noise vector, y_k is measurement noise vector of covariance matrices Q_k and R_k, respectively. y_k is the observed measurement signal. To apply the EKF on the equivalent circuit model of LiFePO4 battery in Fig 1 and the represented discrete-time formed SOC in Eq. (12), the state space equation and the terminal voltage observation equation are derived as follows:

$$x_k = \begin{bmatrix} SOC_k \\ V_{Cp\,k} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 - \dfrac{\Delta t}{C_p R_p} \end{bmatrix} . \begin{bmatrix} SOC_{k-1} \\ V_{Cp\,k-1} \end{bmatrix} + \begin{bmatrix} \dfrac{-\Delta t}{C_n} \\ \dfrac{-\Delta t}{C_{Cp}} \end{bmatrix} .I_{b\,k-1} + w_{k-1} \quad (14)$$

$$y_k = V_{b\,k} = OCV(SOC_k, \alpha_k, \beta_k) - V_{Cp\,k} - R_i.I_{b\,k} + v_{k-1} \quad (15)$$

The computation procedure for the EKF can be applied as followed reference [1].

5. Experimental Verification

To verify the proposed hysteresis modeling algorithm at different SOC regions, the battery is fully charged up to 100% SOC and discharged to 20% SOC. After that, the battery is undergone charging and discharging processes repeatedly at various SOC value. This type of current profile applied for battery test is suitable to verify the hysteresis model as compare to other current profile in which the magnitude of current varies greatly. The Ah counting method is considered as a reference for a comparison between the estimated value and true value. The EKF is used to estimate the SOC of the battery as a main goal of the hysteresis model for any type of battery. To verify the accuracy of the proposed method and the convergence of the EKF, 3 different initial values 60%, 90% and 100% SOC are used, Fig. 3 show results of the SOC estimation and the error between the proposed method and the Ah counting. The SOC error after converging does not exceed 2%.

6. Conclusions

In this study, the hysteresis phenomenon of the LiFePO4 battery is investigated and a hysteresis model is also proposed. From the proposed method, the implementation of RLS for parameter identification and EKF for SOC estimation has been done. The accuracy of estimation, time and labor for battery modeling are improved significantly. The obtained results reveal that the proposed method works accurately and it can be used for the BMS such as electric vehicle and energy storage applications.

References

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[2] L. Ljung, System Identification Theory for the User: Second Edition, USA: Prentice Hall PTR, 1999.