A novel State of Health estimation method for Lithium-ion battery in electric vehicles

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Abstract. To ensure safe operation of lithium-ion battery, precise estimation of its states like state of health (SOH) is indispensable. This paper proposes a novel SOH estimation method for lithium-ion battery in electric vehicle applications. When it’s time to update battery capacity, the estimator extracts historical current and voltage data of last driving event and estimates open circuit voltage (OCV) based on affine projection algorithm. By means of the estimated OCV and the three-dimensional response surface OCV model, the SOH estimator gives the estimation result of the battery capacity. Experiments verify that the proposed estimation method is accurate and robust under different working conditions and different aging states.

1. Introduction

The breakthroughs of lithium-ion battery technology in recent years have pushed its wide applications in automobile industry. Nowadays, lithium-ion batteries, specifically lithium nickel-manganese-cobalt oxide (LiNMC) and lithium iron phosphate (LiFePO₄) batteries, have dominated the automotive power battery industry due to higher specific energy, longer time span and lower self-discharging rate.

To ensure safety of electric vehicles and optimize the energy management strategy, it is necessary to realize effective monitoring of power battery packs during vehicle operation. State of health (SOH), as one of the most important parameters for lithium-ion battery, needs to be estimated accurately by the battery management system (BMS).

The SOH describes the degree of battery aging and is usually evaluated by battery capacity. Therefore, the problem boils down to capacity estimation. Existing approaches include incremental capacity analysis (ICA), differential voltage analysis (DVA), empirical model based method, etc. Unfortunately, for ICA/DVA method, the battery needs to be charged or discharged in constant-current condition [1-2]. To construct the empirical model, time-consuming and laborious accelerating aging experiments under various environment conditions are indispensable. Thus, above limitations restrict applications of pertinent methods. A simple while useful capacity estimation method is dividing the accumulated charge by the state of charge (SOC) variation in a certain period of time [3], where the SOC is obtained from an OCV-SOC look-up table. Hence the critical problems are how to estimate OCV accurately and build a robust OCV-SOC look-up table against different levels of battery aging.

This paper proposes a novel capacity estimation method for lithium-ion battery in electric vehicle operation. The three-dimensional response surface based OCV-SOC model [4] is adopted to capture
the varying relationship between OCV and SOC at different aging levels of the battery and is combined with particle swarm optimization (PSO) algorithm to give the capacity estimation result. As a state-of-the-art optimal algorithm, the PSO method is able to obtain the global optimum very efficiently. Experiments show that the proposed SOH estimation method is accurate and robust.

2. Battery modelling and OCV estimation

The first-order RC equivalent circuit model (ECM), as shown in figure.1, is widely adopted to depict lithium-ion battery dynamic characteristics due to its good balance between simplicity and accuracy [5]. It is comprised of a voltage source, an ohmic resistance $R_o$ and a RC (polarization resistance $R_p$ and polarization capacitance $C_p$) network. The correspondence between the HPPC voltage response and components of the battery model is annotated in figure.1 as well. Here the voltage source represents the SOC and capacity-dependent OCV and can be expressed by the three-dimensional response surface model as follows:

$$OCV(SOC, C_n) = \sum_{i=0}^{n_r} c_i \times (SOC)^i$$

(1)

Figure.1. First-order RC equivalent circuit model of the battery

Figure.2. The three-dimensional response surface model of OCV
In this paper, the polynomial order of OCV with respect to SOC, which is denoted as $n_p$ in equation (1), is set to 5. The polynomial coefficient $c_i$ is a two-order polynomial function of capacity $C_n$. The fitting result of the investigated LiNMC based on HPPC test is shown in figure 2.

According to Kirchhoff’s law, the electrical behavior of the adopted ECM can be expressed as:

$$C_p \frac{dv_p}{dt} + \frac{v_p}{R_p} = i_b$$

(2)

$$v_b = OCV - v_p - i_b R_v$$

(3)

where $v_p$ is defined as the voltage across the RC network, $i_b$ is the outflow current (positive for discharging and negative for charging) and $v_b$ represents the terminal voltage.

By means of z-transformation, the non-linear ECM battery model can be transformed into the following auto regressive exogenous (ARX) model, which is linear and demonstrated below [6]:

$$y_k = \theta^T x_k$$

(4)

$$x_k = [-i_b(k), -i_b(k-1), OCV(k-1) - v_b(k-1), 1]^T$$

(5)

$$\theta_k = [\theta_1, \theta_2, \theta_3, \theta_4]^T = [R_v, -R_v + \frac{T_s}{C_i}, \frac{T_s R_v}{C_i R_i}, \frac{T_s}{C_i R_i}, -1, OCV]^T$$

(6)

where $k$ is the step index. $T_s$ is the data sampling period.

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3. PSO based SOH estimator

In this paper, particle swarm optimization (PSO) algorithm is used to find the optimal battery capacity that best fits the constraints imposed by ampere-hour counting and SOC variation during a period. In general, PSO is an efficient and powerful optimization method, inspired by researches about social behavior of bird herds. In PSO, the set of candidate solutions is defined as numerous particles flying around the given predefined space. Each particle will fly with the combined speed aiming at both “local” and “global” best location during update. When the number of iteration reaches preset value or all particles closely converge to one location, the algorithm stops and the location of the best particle, which gives the lowest fitness function value, is the optimization result.

Assuming $X_i = [x_{i1}, x_{i2}, ..., x_{in}]$ and $V_i = [v_{i1}, v_{i2}, ..., v_{in}]$ are the current location and speed of particle $i$, respectively, $pbest_i = [pbest_{i1}, pbest_{i2}, ..., pbest_{in}]$ is the best location that particle $i$ has once arrived. If $f(X)$

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is the fitness function that needs to be minimized, the current best location of particle \( i \) is determined by:

\[
\text{pbest}_i(t + 1) = \begin{cases} 
\text{pbest}_i(t) & \text{if } f(X_i(t + 1)) \geq f(\text{pbest}_i(t)) \\
X_i(t + 1) & \text{if } f(X_i(t + 1)) < f(\text{pbest}_i(t))
\end{cases}
\]  

(12)

Assuming \( N \) is the number of particles, the best location of all particles \( g\text{best}(t) \) is called global best location and defined as:

\[
g\text{best}(t) = \min \{f(\text{pbest}_1(t)), f(\text{pbest}_2(t)), \ldots, f(\text{pbest}_N(t))\}
\]  

(13)

The speed and location update equations are as follows:

\[
v_{ij}(t + 1) = mv_{ij}(t) + c_1r_1(\text{pbest}_i(t) - x_{ij}(t)) + c_2r_2(\text{gbest}(t) - x_{ij}(t))
\]  

(14)

\[x_{ij}(t + 1) = x_{ij}(t) + v_{ij}(t + 1)
\]  

(15)

where \( v_{ij}(t) \) and \( x_{ij}(t) \) represent the velocity and location component on \( j \)th dimension of particle \( i \) in \( t \)th generation respectively. \( \text{pbest}_i(t) \) is the best location component on \( j \)th dimension of particle \( i \) in \( t \)th generation. \( \text{gbest}(t) \) represents the global best location component on \( j \)th dimension of all particles in \( t \)th generation. \( m \) is the inertia coefficient. \( c_1 \) and \( c_2 \) are the cognitive and social parameters respectively. \( r_1, r_2 \) are both random numbers in range \([0,1]\). The main calculation steps of PSO are listed in Table 1.

| Table 1. Main steps of PSO |
|-----------------------------|
| Step 1: Initialize the velocity and location of all particles. Set local best location \( \text{pbest} \) of each particle as its initial location. Set global best location \( g\text{best} \) as the best location of all particles. Set the maximum number of iterations. |
| Step 2: Adjust velocity and location of each particle according to equation (14) and equation (15). |
| Step 3: Update \( \text{pbest} \) of each particle according to equation (12). |
| Step 4: Update \( g\text{best} \) of particle swarms according to equation (13). |
| Step 5: Check if terminal condition is satisfied. If it is, terminate iteration and return \( g\text{best} \). Otherwise return to step 2. |

The proposed SOH algorithm is shown in figure 3. Firstly, part of the measured current and voltage data are extracted from the last driving event. It needs to be noticed that the data length should be long enough so that distinct SOC variation can be observed. Otherwise, the estimated capacity may not be accurate as expected. Then, estimate the OCV based on AP algorithm and record OCV values of some selected sampling points, which are evenly distributed between the start and end points. Considering the initial guess of OCV may be largely deviated from its true value, the first few estimation results of OCV are not reliable. So the start point defined here doesn’t refer to the “first point” but the point where the OCV estimation gets close to its true value with high confidence. As shown in figure 3, part of measured data before start point are left out for convergence. At last, estimate the battery capacity based on the three-dimensional response surface OCV model and PSO algorithm, aiming at minimizing the following fitness function:

\[
\min_C \sum_{n=1}^{L} \left( \int_{t_{n+(m-1)T}}^{t_{n+mT}} i_b dt - C_n \times (\text{SOC}_{s+m} - \text{SOC}_{s+m}) \right)^2
\]  

(16)

where \( L \) is the number of the sampling points. \( T \) represents the time interval between adjacent sampling points. In this case, battery capacity \( C_n \) is the only optimization variable in the PSO algorithm, where \( X=C_n \). Notice that in equation (19), \( \text{SOC}_{s+m} \) are also functions of battery capacity as they are looked up from OCV-SOC curve, which is picked up from the three-dimensional response surface OCV model according to battery capacity. The concept behind the method is to find the OCV-SOC curve that best fits the equation relationship between \( (\text{SOC}_{s+m}-\text{SOC}_{s+m}) \times C_n \) and
\[
\int_{t_m}^{t_{m+1}} i_s \, dt, \quad \text{both referring to how much electricity is consumed during a given period. The capacity corresponding to the best suitable OCV-SOC curve is the estimation result.}
\]

4. Experiment and verification of the proposed SOH estimation method

The battery test data are generated in the test bench consisting of an Arbin BT2000 tester, a thermal chamber, a computer for user-machine interface and a switchboard for cable connection. The voltage, current, temperature of each cell are recorded at the sampling time of 10Hz. The tested batteries were 8 LiNMC battery cells with 0.94Ah nominal capacity, 3.7V nominal voltage. Each cell experienced impedance test and characterization tests (including static capacity test, hybrid pulse test, resistance test, dynamic stress test (DST) and federal urban dynamic schedule (FUDS) test) under 22°C in different levels of degradation. More details about the battery experiment are available in [5].

Figure 4 demonstrates the validation results of the proposed SOH estimation algorithm. From figure 4 (a), it can be seen that as the number of aging cycle increases, the battery capacity decreases gradually. In addition, whatever the working condition is, the estimated capacity is close to the real value calibrated by coulombic counting method, verifying the robustness of the SOH estimator. To clearly show how accurate the estimation method is, figure 4 (b) plots the relative error between the estimated and real capacity. It is obvious that the relative error is below 1% for all working conditions under different aging states. The mean relative capacity estimation error for HPPC, DST and FUDS at different degradation levels are 0.51%, 0.46% and 0.39% respectively, more accurate than the method reported in [8], which didn’t incorporate the influence of capacity on OCV-SOC look-up table and the estimation error can reach 1.66%. The proposed method adopts the three-dimensional response surface model to accurately capture the changing characteristics of OCV-SOC relationship as battery ages and exploits advanced PSO algorithm to find the optimal capacity value that mostly make the SOC change from OCV-SOC look-up table and current integration match. Thus, both the accurate model and
optimization algorithm ensure the accuracy of the SOH estimator. At last, it is worthy to mention that the SOH estimator doesn’t need to be implemented online considering the slow varying feature of battery capacity as battery degrades.

![Figure 4](image.png)

(a) Capacity estimation results at different aging states under different working conditions (b) Relative error

5. Conclusion

This paper presents a novel SOH estimation method for lithium-ion battery in electric vehicle applications. Based on the accurate three-dimensional response surface model of OCV, the SOH estimator is triggered periodically offline to re-calibrate the battery capacity as battery ages. Experiments show the capacity estimation error is below 1% whatever the aging state and working conditions are.

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