SOH Estimation of Lithium-ion Batteries for Electric Vehicles

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Abstract

Accurate estimates of the state-of-health (SOH) for rechargeable batteries provide a significant value to the management of any operation involving electrical systems. This is especially important for transportation systems, where unexpected battery performance may lead to catastrophic failures. This paper performs experiments aiming at analyzing Lithium-ion battery performances with aging due to different temperatures and charging-discharging rates, and the optimum working areas of temperature and charging-discharging current are determined. In addition, the cycle life tests of battery are launched based on the simulations of battery performances under typical urban driving cycles using ADVISOR, and after the inspection of the results, a new SOH prediction model is proposed. Finally, in comparison with the experimental results, it is shown that the proposed method could be valid and effective in estimating battery SOH.

Keywords

State-of-health, Capacity attenuation, Charging-discharging rate, Electric Vehicle

1 Introduction

Batteries are core part of many important devices and always critical to the performance of the overall system. Failure of the battery often results in catastrophic effects, especially in Electric Vehicle (EV) and aerospace systems. Due to complex vehicle operating conditions, frequent charging and discharging and high working temperature will intensify the attenuation of battery. An efficient method for battery cycle life prediction would greatly improve reliability of the power system.

In the electrified domain, researches have looked at various failure modes of the battery systems, different diagnostic methods have been evaluated [1]. Other works have concentrated more on the prognostic perspective [2]. Impedance spectrometry has been used to build battery models for cranking capability prognosis [3]. State estimation technics, like the Extended Kalman Filter (EKF), have been applied for real-time prediction of (State-of-Charge) SOC and SOH (State-of-History) of automotive batteries [4]. Automated reasoning schemes based on neural fuzzy and decision theoretic methods have been applied to fused feature vectors derived battery sensor to arrive at estimate of SOC and SOH [5].

The following sections will expand more on the chosen battery cycle life prediction model, the experimental setup, results analysis and finally the conclusions presented.

2 Overview of the experiment

2.1 Used lithium-ion cells and equipment

The cells used are lithium-ion power cells: each cell outputs a nominal capacity of 4.8 Ah and has a full charge voltage of 4V. Its chemistry is based on a natural graphite negative, a $LiFePO_4$ positive and $LiFL_6$ electrolyte.

The equipment applied is NBT battery test system, temperature sensors and a climatic chamber with a temperature fluctuating between -30℃ and 60℃, as illustrated in Figure 1.

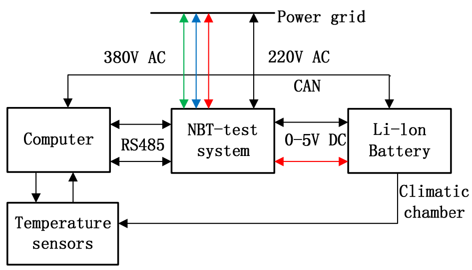

Figure 1. Equipment connection diagram

2.2 Experiment procedure

The battery performance is influenced by the charging (*ch*) and discharging (*disch*) history and it can also drift dramatically with temperature variation.

Moreover, in practice load current of the battery changes when an EV (electric vehicle) accelerates or decelerates. Thus, different temperatures and charging-discharging (*ch-disch*) rates, as well as the cycle life tests must be concerned in the experiment.

2.1.1 Different temperature test

In this paper, NEDC (New European Driving Cycle) is selected as the test driving condition, from which we can obtain the rate distribution of *ch-disch* current, as shown in Figure 2. On this basis, the experiment temperature is set to be 20℃, 30℃ and 40℃; the *ch* current is 5C.

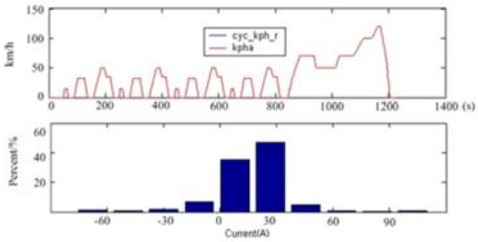

Figure 2. NEDC *ch-disch* rate distribution

And the overall measure procedure is described by the following steps:

1. Charge the cell with 0.5C current till the voltage reduces from nominal value to 3.0V, standing for 30min;
2. Charge the cell with 5C current till the voltage comes up to 4.95V, standing for 30min;
3. Discharge the cell with 1C current till the voltage decreases to 3.0V, standing for 30min;
4. Repeat step 2 and 3 of the experiment till the cell capacity accounts for 80% of the nominal value.

2.1.2 Different current test

In practice, the utmost work temperature of EVs is around 40℃, which hereby is set as the experiment temperature. And according to the NEDC current rate distribution, *ch* current are determined to be 5C and 10C, while *disch* current are 10C and 20C.

The charging procedure is similar to the above process except for adopting different current, the main difference lies in the discharging procedure, where the third step here is discharging the cell with 1C, 10C and 20C respectively till the voltage attains a certain value (1C vs. 3.0V whereas 10C and 20C vs. 2.4V).

3 Battery failure prediction model

3.1 Theoretical analysis of failure prediction model

Battery Life is defined as: the quantity of cycle times when battery capacity attenuates to a certain percentage of the nominal value at certain *ch-disch* rate, namely, battery capacity attenuation rate. Generally, the two main factors which cause the battery capacity attenuation are temperature and *ch-disch* current. In addition, fault model can be concluded to cumulative damage-reaction theory life model, including Arrhenius, Inverse Power Law and Eyring as well as damage cumulative model. Based on the Arrhenius model, the battery attenuation can be expressed as:

$$\frac{dX}{dt} = f(I)e^{-\frac{\Delta E}{KT}} = f(I)f(T) \tag{1}$$

Where $f\,(I)$ and $f\,(T)$ are functions of current and temperature respectively, ΔE is activation energy, eV ;K is Boltzmann constant, 0.8617×10-4 eV/K; T is the absolute temperature, K.

On the integration of Equation (1), can deserve:

$$\int_{X_0}^{X_L} dX = \int_{t_0}^{t_L} f(I)f(T)dt \tag{2}$$

$$X_L - X_0 = f(I)f(T)(t_L - t_0) \tag{3}$$

Let $C_r = X_L - X_0$, $n = t_L - t_0$; then

$$C_r = f(I)f(T)N \tag{4}$$

In which, C_r is battery capacity attenuation rate, N is the cycle times.

Furthermore, due to damage cumulative model, the relationship between capacity attenuation rate and cycle times can be described in power function of:

$$C_r = mN^n \tag{5}$$

Where m, n is the model parameters, which will be determined later.

3.2 Data processing and analysis

With the aid of the testing data, the analysis of the influence of temperature and charging-discharging current on battery capacity attenuation rate (Cr) is carried out through curve fitting method, as shown in Figure3 (a)-(d).

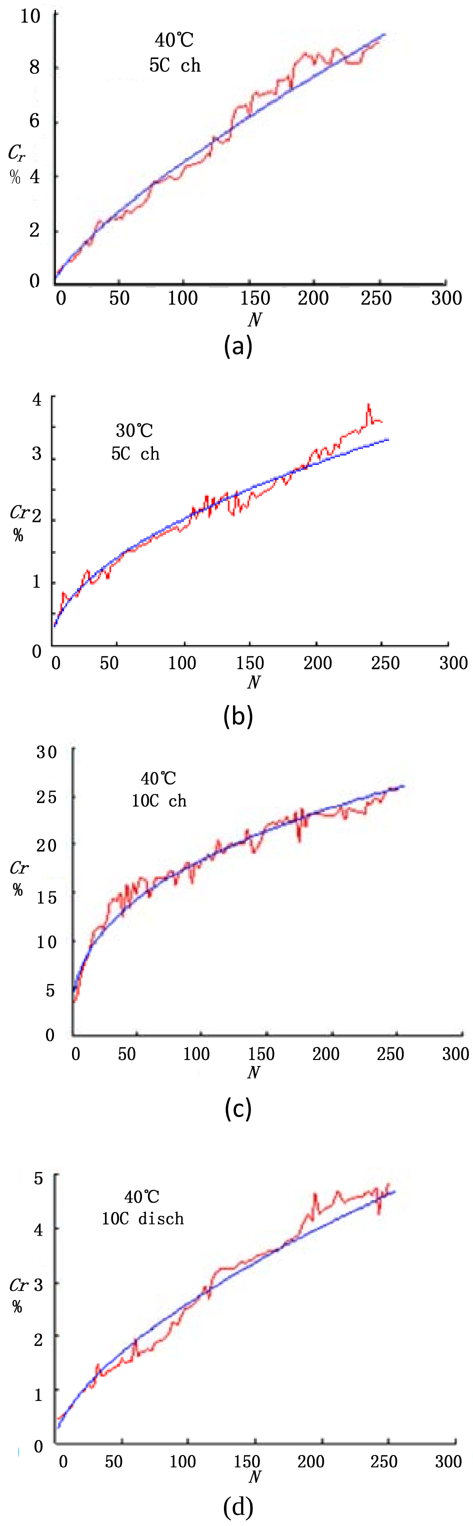

Figure 3. Curve fitting of C_r and N under different temperature and current

From Figure3 (a) and (b), we can observe that temperature is a critical factor affecting C_r, which has a relatively low level around 30℃, and C_r increases either the temperature arises or declines, however higher temperature has a more significant influence on battery attenuation.

And Figure3 (a), (c) and (d) depict the impact of *ch* and *disch* current on *Cr*, the influence of *ch* current is far greater than *disch*, as illustrated in Figure(c) and (d); and *Cr* rises with the increases of *ch-disch* current.

3.3 Model parameters determination

On the basis of the cumulative damage-reaction theory, the parameter *m* and *n* can be obtained through fitting method.

Table1 Curve fitting values of *m* and *n*

P	T=293K I=5C	T=313K I=-10C	T=313K I=-20C	T=313K I=10C
m	0.3334	0.2548	0.6361	4.604
n	0.6045	0.6298	0.5885	0.3745

Table1 shows that *m* and *n* are closely related to temperature *T* and current *I*, so Equation (5) can be expressed as:

$$C_r = m\,(I_{ch}, I_{disch}, T)\,N^{n(I_{ch}, I_{disch}, T)} \tag{6}$$

Afterwards, three groups of curve fitting are carried out, of which each one of the three variables (I_{ch}, I_{disch}, T) is taken as the only variable respectively with the other two don't change.

And finally, through further amendment with the experimental data, Equation (6) can be expressed as:

$$C_r = 0.01656\, I_{ch}^{0.3428}, I_{disch}^{0.1905} * e^{\frac{942.67}{T}} N^{14.235 I_{ch}^{0.1595} I_{disch}^{0.0257}} * e^{-\frac{1059.63}{T}} \tag{7}$$

4 Model and Actual comparison

As described in the section, battery attenuation can be evaluated through Equation (7), and this prediction model is confirmed to be effective and feasible compared with the experimental observed results, as shown in Figure4.

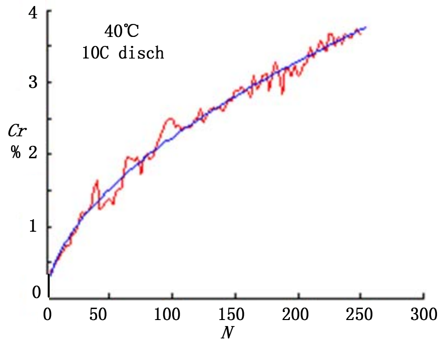

Figure 4. Prediction and experimental results comparison

5 Conclusions

The combined curve fitting and cumulative damage-reaction theory life model method has significant advantages over conventional methods of battery capacity attenuation monitoring.

Ageing of lithium-ion cells involve in complex electro-chemical reactions internal, its state variables are hard to detect and its performance is highly ambient environment and load current related. The battery capacity attenuation model presented provides a simplified method to estimate the capacity attenuation rate, not only for the failure prediction of battery in EVs but also suitable for other battery mounted machines.

Further studies are planned to be performed, showing how more extreme conditions of temperatures and charging-discharging current may impact on the cycle life of lithium-ion batteries.

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