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A neural network based state-of-health estimation of lithium-ion battery in electric vehicles

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Abstract

As one of the main promising power sources in electric vehicles (EVs), lithium-ion battery plays an important role in EVs' power system. Its state-of-health (SOH) estimation is a key technology in the battery management system (BMS). Many battery parameters can reflect the battery's health, like internal resistance, internal capacity, etc. In this paper, we use maximum available capacity to indicate the battery's SOH based on a back propagation (BP) neural network. The main contributions of this paper include: (1) a direct parameter extraction method by HPPC (Hybrid Pulse Power Characterization) test is employed to identify the battery parameters of the first-order equivalent circuit model. (2) The parameters can be used to train the three-layer BP neural network, therefore the structure and parameters including weights and thresholds of the network can be determined. This well-trained neural network is used to estimate the SOH. (3) The static and dynamic current profile tests are carried out to verify the accuracy of the training results of the proposed neural network. The experimental results indicate that the proposed neural network based estimation method can present accuracy and suitability for SOH estimation with low computation cost.

Keywords: Lithium-ion Battery; State-of-health; Parameter Identification; Neural Networks.

1. Introduction

Electric vehicles (EVs) have been developed rapidly in recent years. The lithium-ion batteries have become one of the most promising power sources of EVs due to the advantages of high energy density, environmental protection, long cycle life, etc [1]. As other batteries, issues like aging and fault occur in lithium-ion batteries as time goes and the batteries are circularly used. In order to ensure efficient and safe operation, prevent battery from over-charging and over-discharging and extend the lifespan of the lithium-ion battery system, it is necessary and important to estimate the battery's state-of-health (SOH). However, various ambient temperature, different current profiles, complex driving condition and other factors all have an influence on the SOH. The unknown weight and nonlinear behavior of each influence factor make it quite difficult to estimate SOH accurately.

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The variation of SOH is concretely reflected in the variation of internal resistance, capacity and also some other indicators. Extensive studies have been carried out for the SOH estimation in recent years. Battery internal resistance has been used to monitor the SOH in Refs.[2][3][4]. These papers analyzed the relationship between the resistance and capacity, and showed low computational effort and good robustness, but the disadvantage is that few influence factors are considered. SOH can be estimated by probabilistic and statistic methods, which are shown in Refs.[5][6]. This type of methods combines mathematical knowledge with empirical knowledge to construct an empirical or semi-empirical model, it will cost much time to obtain plenty of experimental data. The neural network (NN) is an effective way to estimate SOH. Ref.[7] presented a model based on EIS, and describes a method of SOH monitoring, which uses recurrent neural network to predict the deterioration in battery performance. Ref.[8] used a probabilistic neural network to estimate SOH, where the parameter identification was not considered, while it is shown in this paper. The NN is a kind of statistical model which needs large numbers of experimental data to train in order to acquire ideal results. It doesn't need to know the accurate electrochemical reaction and is trained by a learning algorithm repeatedly till the estimation error is less than the preset threshold.

In this paper, we propose a NN based method to estimate SOH. A direct parameter extraction method is employed to identify the parameters of the first-order equivalent circuit model (ECM). Then a three-layer back propagation (BP) neural network is proposed to estimate SOH, whose inputs are the parameters of the first-order ECM and output is the current value of SOH. Final, experiment is designed to verify the accuracy of the proposed neural network. The structure of the paper is listed as follows: the definition of SOH and model introduction including battery model and NN model are given in section 2. The identification algorithm is introduced in section 3. In section 4, we give the experiment procedure and verification result of the proposed method. Lastly, the conclusions are discussed in section 5.

2. Model Description

2.1. Definition of SOH

SOH can be defined as the ratio of current maximum available capacity to the nominal capacity which can be impressed as follows [9]:

$$SOH = \frac{Q_{now}}{Q_{new}} \times 100\% \tag{1}$$

where Q_{now} represents the maximum available capacity, Q_{new} represents the nominal capacity. When SOH drops below 80%, we consider the battery unserviceable because the capacity degradation data exhibit a trend with exponential decay after crossing the 80% threshold [10].

2.2. Battery Model

The battery models can be generally classified as the electrochemical model [11], the equivalent circuit model [13][14] and the neural network model [7][8][12].

2.2.1. First-order ECM

The first-order ECM is one of the most popular ECMs used in the battery's state estimation. As is shown in Fig.1 (a), $OCV(t)$ represents the open-circuit voltage. $U_L(t)$ is the terminal voltage of the battery. $U_p(t)$ is the voltage of the RC parallel network, $I_L(t)$ is the total current at time t, which is positive when battery is charging and negative when discharging. And R_0 represents the ohmic resistance. The parallel of R_p and C_p indicates the polarization effect.

2.2.2. *Neural Network Model*

The NN model is shown in Fig.1 (b), and it consists of three layers: input layer, hidden layer and output layer. In this model, the inputs are SOC, and the ECM parameters including ohmic resistance R_0, polarization resistance R_p and polarization capacity C_p. $\mathbf{iw}_{i,j}$ is the matrix of connecting weight from input layer to hidden layer. $\mathbf{lw}_{i,j}$ is the matrix of connecting weight from hidden layer to output layer. $\mathbf{b}_1$, $\mathbf{b}_2$ are the threshold matrix of hidden layer and output layer, respectively. In this paper, we choose back propagation neural network (BPNN) to train the input data. The output of this model is expressed in equation (2).

$$SOH(t) = \text{purelin}(\mathbf{lw} \cdot (\text{logsig}(\mathbf{iw} \cdot \mathbf{p} + \mathbf{b_1})) + \mathbf{b_2}) \tag{2}$$

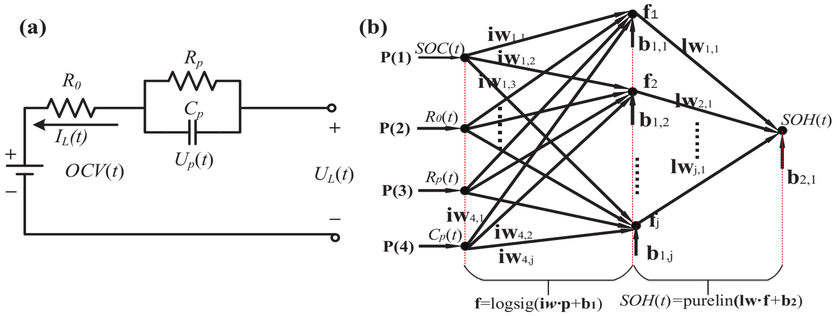

Fig.1.(a) First-order ECM. (b) The NN model structure.

3. Parameter Identification

The HPPC test is usually used for model parameter identification and model accuracy verification. The part graph of HPPC profile in a circle is shown in Fig.3. U_0 in Fig.2 (b) is the voltage of R_0. The ohmic resistance R_0 can similarly be seen as the ratio of dropout voltage and dropout current when the current is changed suddenly, which is expressed as equation (3). R_p and C_p can be reflected by the continuous voltage change after the voltage leaps and they can be estimated by least squares fit. The formula that needs to fit is shown as equation (4) [14], which only has R_p and C_p two variables:

$$R_0 = \frac{\Delta U_0}{\Delta I_L} \tag{3}$$

$$U_p(k+1) = \exp\left(\frac{-\Delta t}{R_p C_p}\right) \cdot U_p(k) + R_p I_L(k) \cdot \left(1 - \exp\left(\frac{-\Delta t}{R_p C_p}\right)\right) \tag{4}$$

where Δt means sampling time. $U_p(k+1)$, $U_p(k)$ and $I_L(k)$ are the initial data processed by discretization.

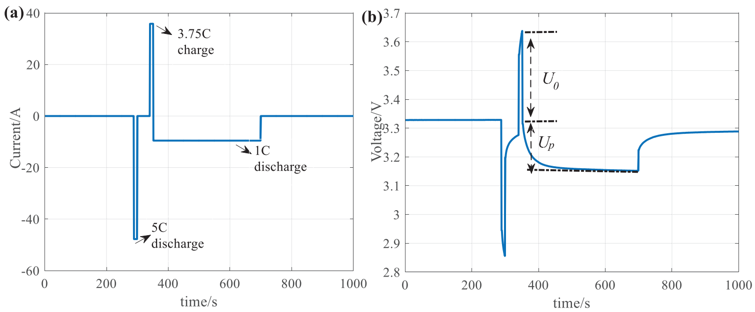

Fig.2. Part graph of HPPC profile. (a) Current profile. (b) Voltage profile.

4. Experiment and Result Discussion

4.1 Test Bench and Experiment Design

The test bench is shown in Fig.3 (a). The host computer is used for online experiment control and data record. The battery test equipment is responsible for charging and discharging the batteries according to the required current profiles.

We experiment with 10 $LiFePO_4$ batteries in different aging degrees, which type is IFP-1865140. All batteries' reference capacity is 10Ah. The SOH of each battery are shown in Table 1. All the tests were operated at 25℃. Static capacity tests are taken for getting the current maximum available capacity of the batteries so that we can compute the value of SOH. The average capacity of the three tests is taken as the maximum available capacity of the battery. After resting for an hour, a HPPC test is taken to identify model parameters, whose current profile and SOC variation are shown in Fig.3 (b).

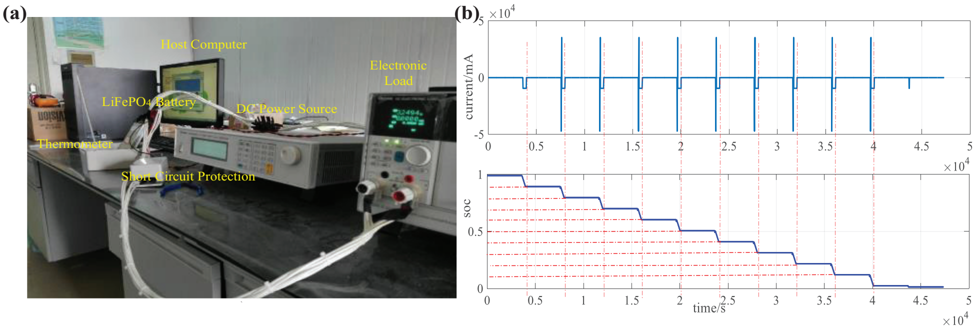

Fig.3. (a) Test bench. (b) Current profile of the HPPC test and the SOC changing curve in the HPPC test.

Table 1. SOH information about all test batteries.

Battery order	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
SOH/%	103.30	99.71	95.90	93.10	74.00	102.90	99.49	95.61	94.30	81.68

4.2 SOH Estimation Analysis

The information of all batteries' SOH can be looked up in Table 1. The relationship between model parameters, SOC and SOH are shown in Fig.4. As we can see in Fig.4 (a), it is easy to conclude that the ohmic resistance R_0 is increased when SOH is reduced. And when the SOC range is between 20% and 90%, R_0 roughly increases by SOC decreases. But the rules about R_p and C_p are not as clear as R_0. R_p and C_p change with SOC and SOH in a nonlinear way which we can't acquire by simple observation. Since the relationship is difficult to get, BP neural network shown in Fig.2 is needed here to find the relationship between these inputs and SOH.

For SOH estimation, we use 5 batteries (#1 ~ #5) to train the NN, and other 5 batteries (#6 ~ #10) to test the estimation accuracy of the NN. The test results are shown in Fig.5. It is noted that SOH is considered identical in a cyclic. The errors in Fig.5 (b), (d), (f), (h) and (j) equal the amplitude of the difference values between the estimated values and measures values. From these histograms, we can see the maximum error is 7.2%, lower than 8%, and most errors are lower than 5%. The average value of simulation outputs is considered as the current SOH of this battery. The results of SOH by averaged value calculation are listed in Table 2. On the other hand, for a NN, a large data base and accurate parameter identification results are needed in the beginning for training a NN. If more data is used to train the NN, prediction error will be lower.

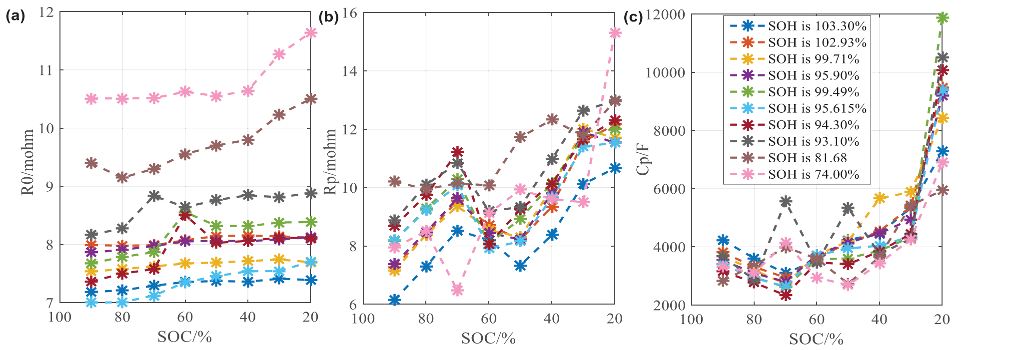

Fig.4. (a) Relationship diagram of R_0, SOH and SOC. (b) Relationship diagram of R_p, SOH and SOC. (c) Relationship diagram of C_p, SOH and SOC.

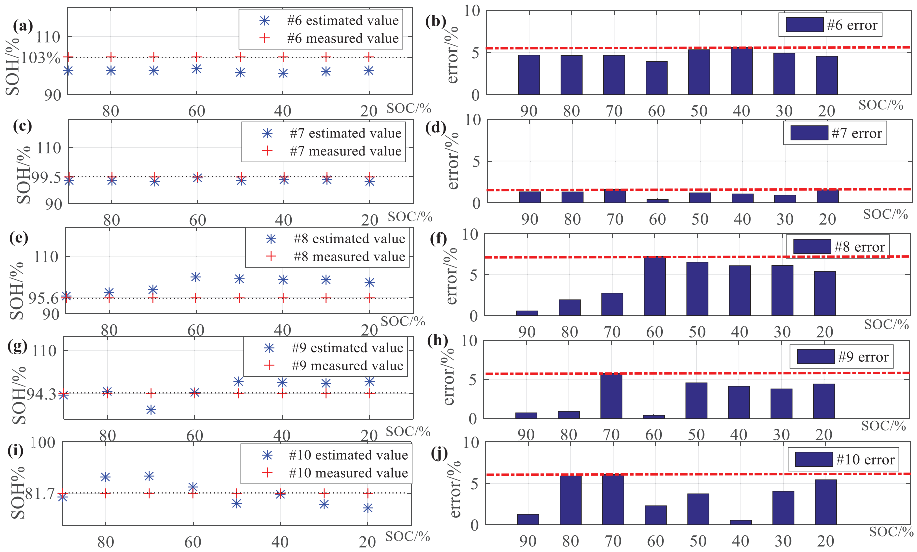

Fig.5. (a),(c),(e),(g),(i): the SOH estimation results of battery #6, #7, #8, #9,#10,respectively. (b),(d),(f),(h),(j): the histograms of estimation error of battery #6, #7, #8, #9, #10, respectively.

Table 2 Estimation Results about Test Batteries.

Battery Order	#6	#7	#8	#9	#10
Measured SOH/%	102.90	99.49	95.61	94.30	81.68
Estimated SOH/%	98.16	98.32	99.98	95.74	81.71

5. Conclusion

A simple method estimating battery's SOH based on BP neural network is proposed in this paper. In this method, with several parameters of the first-order ECM, we can estimate the value of SOH using a three-layer BP neural network. The proposed method has 3 characteristics: (1) low computation cost (the computation time of training the NN is 21ms). (2) Low memory requirement. (3) Easy to understand. The accuracy of result is dependent on the accuracy of identification algorithm, the quantity of training data, the precision of ECM model which is chosen, the test profiles and etc. The training rate depends on the learning algorithm, the numbers of layers and neurons, etc. The error during the work is inevitable because of the error initial sampling data, algorithm error and the inaccuracy of the NN model. So the outputs shall be filtered before being used to computing the final SOH value of a battery.

Copyright

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