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State of Charge Estimation Based on State of Health Correction for Lithium-ion Batteries

Yiduo Zhu, Fuwu Yan, Jianqiang Kang and Changqing Du

Abstract- **In most studies, the state of health (SOH) effect is rarely considered in state of charge (SOC) estimation of the battery. The estimation error gradually increases in the late decline of lithium battery. In this study, the SOC estimation method based on SOH correction and the back-propagation neural network optimized by mind evolutionary algorithm (MEA) is proposed. First, SOH is estimated based on Thevenin battery model and BP neural network. Then, together with the current, voltage and temperature, the SOH is added to the input of the BP neural network, battery capacity can be estimated as the output of the neural network. The next, the initial weights and thresholds of the BP neural network are optimized by the MEA algorithm to achieve better estimation results. The application range of SOC estimation method is further broadened for both the new and old battery.**

I. INTRODUCTION

The estimation of SOC is the basic function of BMS, but most of the current estimation methods are suitable for new batteries or pre-recession batteries. In the late decline of lithium battery, the estimation error gradually increases, mainly due to the fact that the effect of SOH on SOC is unconsidered.

SOC estimation methods include the Ampere-Hour integration method, open circuit voltage method and a variety of data fusion algorithms. The commonly used methods of data fusion include correction, weighting,sliding mode variable structure, neural network, fuzzy algorithm and Kalman filter. Chaoui[1] presented an input time-delayed neural network to estimate both state of charge (SOC) and state of health (SOH) for lithium-ion batteries. Previous battery's voltage and current data were used as input of the neural network. A large amount of experiment on LiFePO4 battery are done to evaluate the high accuracy of the method. Liu[2] proposed a nonlinear optimal compensative state and observation model to estimate the battery SOC. An adaptive sigma Kalman filter algorithm were used to identify the model parameters. Both the model and the algorithm were proved to be accurate and effective by experiment results. Cho[3] employed an equivalent circuit model for SOC estimation. An adaptive estimator which based on the combination of current integration and battery model was employed. Chen[4] employed a combined battery equivalent circuit model to estimate the battery SOC. An adaptive gain sliding mode observer was used to minimize chattering levels and compensate modelling errors. Ernesto[5] researched the dynamic one-dimensional modeling and simulation of Li ion batteries. The model can be used to predict battery electrochemical variables and analyze the internal behavior of the battery under different discharge rates.

SOH reflects the decay of battery capacity, with the main characterization parameters such as the capacity and internal resistance. Most of the models and algorithms for battery SOH research are based on the two parameters. The neural network algorithm can make up the error of the model by increasing the sample data, so as to improve the accuracy of the estimation. However, the geometric growth of computation caused by a large amount of data learning also affects its practical application.

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Yiduo Zhu is with Hubei Key Laboratory of Advanced Technology for Automotive Components，Wuhan University of Technology，Wuhan 430070，China and Wuhan Technical College of Communications ，Wuhan 430065，China.

Fuwu Yan, Jianqiang Kang and Changqing Du are with Hubei Key Laboratory of Advanced Technology for Automotive Components，Wuhan University of Technology，Wuhan 430070，China.(Corresponding author: cq_du@whut.edu.cn (C. Du) Tel: +86 13477059810, Fax: +86 27 87879468)

Zhou [6] proposed a battery remaining useful life (RUL) prediction approach based on online support vector regression. Combined prediction with multi-models involving offline and online algorithms was realized to achieve improved prediction capacity. Saha[7] and Benjamin[8] proposed a particle filter algorithm to estimate SOH and predict RUL. The effect of the self-recharge phenomenon was determined and isolated simultaneously with the life cycle model. Pang [9] used time interval to equal discharge voltage difference as a battery health indicator (HI). The Gaussian process regression (GPR) algorithm was utilized for RUL estimation, and the confidence interval for the RUL value was provided. Jiang [10] selected the same HI. A relation model of extreme learning machine (ELM) based on the time interval to equal discharge voltage and capacity fading was built, and a prediction model of ELM based on the time interval to equal discharge voltage was proposed. Zhou[11] further proposed a combined model for RUL prognosis. Empirical model decomposition (EMD) and autoregressive integrated moving average (ARIMA) were considered in the combined model. Wu[12] utilized the feed-forward neural network (FFNN) and importance sampling (IS) to estimate the RUL of a lithium-ion battery online. FFNN was used to simulate the relationship between RUL and the charge curve, and IS was employed for FFNN input selection. Wang[13] assessed capacity degradation by adopting a state-space model for lithium-ion battery capacity. The model was solved by using a spherical cubature particle filter.

Analysis of previous studies indicates that neural network algorithms are seldom used to predict battery state. The main reason is the extensive algorithmic calculation required for online application. With the improvement of computer computing power and the application of remote monitoring technology, the above problem is solved. As we all know, the neural network algorithm has significant advantages. The algorithm can compensate for the error of the model by increasing the sample data and learning frequency, thereby improving the accuracy of the estimation. neural network algorithm also can be used to estimate of heat generation [14].

In this study, a novel method is proposed to estimate the SOC of lithium-ion batteries. The method has 2 steps: first, estimate SOH based on Thevenin battery model and BP neural network which discussed in detail in Section 4.1. Second, estimate SOC based on mind evolutionary algorithm （MEA）with 4 parameters including charge or discharge voltage, charge or discharge current, temperature and SOH from first step. The contribution of this study is the establishment of a method with merits of high precision and simplicity. This study also provides a theoretical basis for online SOH and SOC estimation.

II. THEORETICAL BACKGROUND AND EXPERIMENT

MEA draws on the idea of group and evolution in genetic algorithm, and introduces the operation of similartaxis and dissimilation. Through these operations, the training and parameter optimization of neural network are carried out, which shows great superiority in solving the premature problem of genetic algorithm. The basic elements of the MEA are: environment, individual, winner, group, superior sub-group, temporary sub-group, local billboard, global billboard, attracting domain and so on. Due to the application of subgroups, mind evolutionary algorithm has faster convergence rate than the other neural network algorithm. The steps to implement the MEA includes 4 steps: initialization, similartaxis, global competition, dissimilation.

Commercial Li(NiCoMn)O2 cylindrical 18650 lithium-ion batteries were provided by Tianjin Lishen Battery Company. The PE material is Li(NiCoMn)O2, and the NE material is graphite. The nominal capacity is 2.6 Ah. The charging and discharge cutoff voltages are 4.2 and 2.75 V, respectively. The multi-channel test equipment (model number CT4008) was provided by Tianjin NEWARE Electronics Company. The test temperature controlled by environmental chambers was stable at 25℃. The reference performance test (RPT), which includes capacity, hybrid pulse power characteristic, and incremental capacity (IC) tests, was used in accordance with the USABC test protocol [15].

Several batteries were cycled in the SOC range of 0–0.3, 0.4–0.7, and 0.7–1 under discharge rates of 1C and

2C. The RPT test was performed after every 150 cycles. The experiments were stopped when 20% of the capacity of the batteries was consumed (from 2.6 Ah to 2.08 Ah). The experiments aimed to examine the effect of SOC cycle range on battery degradation and battery SOH prediction. Table I shows a matrix of the cycle aging test.

Table I. Cycle aging test matrix

Battery number	SOC range	Discharge rate	Cycle count
A	0–0.3	1C	4200
B	0–0.3	2C	4200
C	0.4–0.7	1C	4200
D	0.4–0.7	2C	4200
E	0.7–1	1C	4050
F	0.7–1	2C	2850

III. ESTIMATION AND DISCUSSION

A. SOH estimation based on Thevenin battery model

The Thevenin model is widely used in the study of battery exterior properties. The model can also be used to study battery degradation. Taking the first-order Thevenin battery model as an example[16], the terminal voltage of the battery U_k has the following relationship with the internal resistance R as shown in Eq.1.

$$\begin{cases} U_k = OCV(Z_k) - Up - iR \\ \dfrac{dUp}{dt} = -\dfrac{Up}{RpCp} + \dfrac{i}{Cp} \end{cases} \quad (1)$$

OCV is open circuit voltage. i is (dis)charge current. Up 、 Rp 、 Cp is the battery polarization voltage, polarization resistance and polarization capacitance, respectively. The model parameters can be identified by HPPC test method. In the real vehicle application, BMS control the equalizer which installed between the individual battery to simulate the HPPC test pulse. The above parameters changes with the aging of the battery, so three parameters including incremental ohmic resistance ΔR , incremental polarization resistance ΔRp and decremental polarization capacitance ΔCp are used for the battery SOH estimation in this work. Combined with the conclusion of the above experiment, four factors including the ambient temperature, discharge current, discharge cut-off voltage and the cycle interval are also taken into account in the battery SOH estimation. Therefore, in the construction of the neural network model, the three parameters and the four factors are seven variables of the neural network input, and the battery capacity is the neural network output. The network structure is a three-tier structure. The offline training data of the neural network comes from above experiment, and the online testing data comes from NEDC working condition experiment. The frame of the battery SOH online estimation by neural network model is shown in Fig.1.

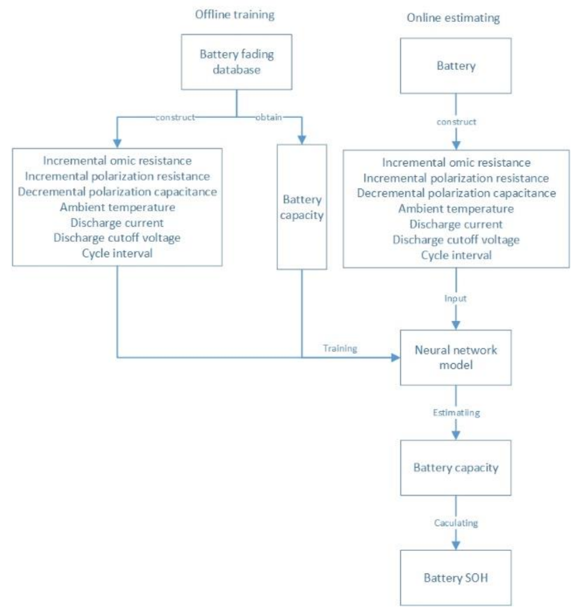

Fig.1 The frame of the battery SOH online estimation by neural network model

The incremental ohmic resistance ΔR , incremental polarization resistance ΔRp and decremental polarization capacitance ΔCp are calculated according to Eq.2.

$$\begin{cases} \Delta R = R^k - R^0 \\ \Delta Rp = Rp^k - Rp^0 \ (k = 1, 2, \ldots, n) \\ \Delta Cp = Cp^0 - Cp^k \end{cases} \quad (2)$$

R^0 、 Rp^0 、 Cp^0 is the initial polarization voltage, initial polarization resistance and initial polarization capacitance of the battery, respectively. R^k 、 Rp^k 、 Cp^k is the battery polarization voltage, polarization resistance and polarization capacitance of the NO.k battery standard test after certain cycles, respectively.

BP neural network is used for SOH estimation based on Thevenin battery model. The network structure is 7-12-1, which represents the number of neurons of input layer, hidden layer and output layer is 7,12 and 1, respectively. The number of hidden neurons is still determined by multiple trying. After the full training, the fading data of battery E is used to verify the effect of neural network SOH estimation. The results are shown in Fig.2.

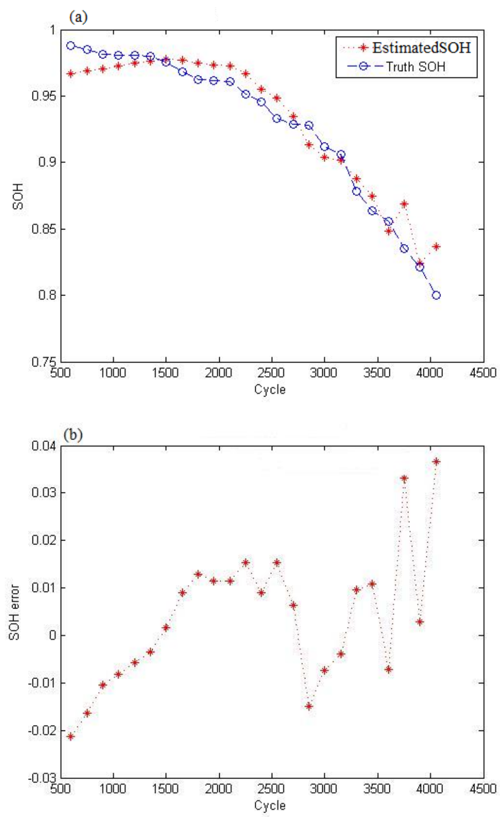

Fig.2 BP neural network SOH estimated (a) result and (b) error of battery E

The blue circle in Fig.2 (a) shows the actual SOH, which is calculated from the measured capacity, and the red star represents the SOH estimated by the BP neural network. It can be seen that the estimated results well track the changes of battery SOH. The red star in Fig.2 (b) shows the estimated error, which is the difference between the estimated SOH and the actual SOH. It can be seen that all the errors are less than 0.04.

B. SOC estimation based on MEA

The structure of BP neural network for lithium-ion battery capacity estimation includes 3 layers which are determined as follows: the input layer has three neurons including charge or discharge voltage, charge or discharge current and temperature; hidden layer has 7 neurons (after several training adjustments); output layer has only one neuron - the battery capacity (also can be directly converted to the battery SOC).

The MEA-BP algorithm is designed to optimize the initial weights and thresholds of BP neural networks by using the MEA. Firstly, the solution space is mapped to the coding space according to the structure of BP neural network, and each code corresponds to a solution (individual). As described above, the structure of the BP network in this study is 3-7-1, and the coding length is $3 \times 7 + 7 \times 1 + 7 + 1 = 36$. The reciprocal of the mean square error of the training data set is chosen as the scoring function of the individual and the group. MEA is used to iterate and output the best individuals, which are used as the initial weights and thresholds to train the BP network.

The charge and discharge data (240000 groups) of the new 2.6Ah lithium battery under different working conditions were used as the training data of the neural network, and then the discharge data (1000 groups) of fully charged new battery under 25 ℃ and the new European driving condition (NEDC) were used as the test data. MEA-BP neural network and general BP neural network are used for SOC estimation respectively. The errors are shown in Fig.3.

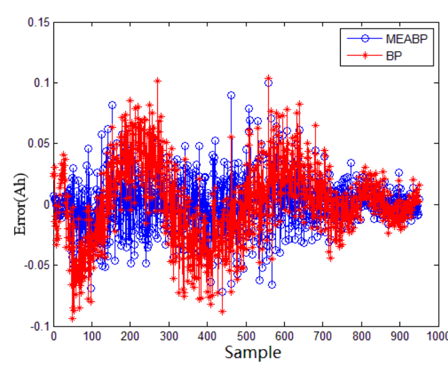

Fig.3 Estimation error of MEA-BP and general BP neural network

As shown in Fig.3, it can be seen that the MEA optimization algorithm can effectively improve the BP neural network estimation results, and the estimation errors are better than the general BP algorithm. The absolute values of the estimated errors are averaged according to the different SOC interval, and the average error distribution histogram related to SOC is shown in Fig.4. Fig.5 shows the optimized average error distribution histogram related to SOC. Fig.6 shows the comparison of average error distribution related to SOC before and after optimized. It can be seen that in the middle of the SOC interval estimation error is large, for battery voltage changing slowly in that interval.

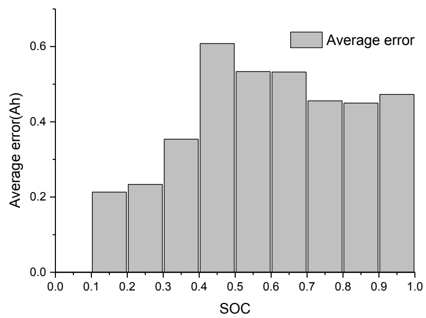

Fig.4 Average error distribution related to SOC

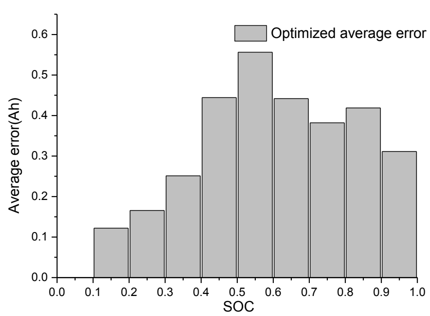

Fig.5 Optimized average error distribution related to SOC

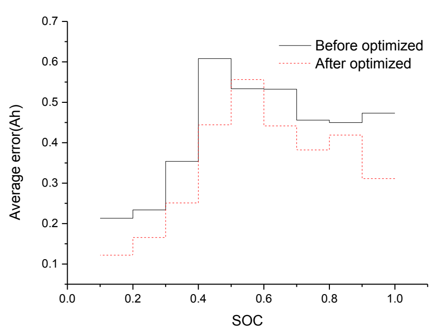

Fig.6 Comparison of average error distribution related to SOC before and after optimized

C. SOC estimation based on SOH correction

In addition to voltage, current and temperature data, the battery SOH is added to the input layer of the network. The training amount of neural network is increased, and the number of hidden layer nodes should be appropriately increased according to the actual situation in order to achieve the relative balance between accuracy and time cost. In practical application, due to the large amount of training, the BMS computing capability may be insufficient. So this correction method needs to use the remote monitoring system as the server to compute, then transfer the results back to the BMS.

The battery is tested under the NEDC working condition and the battery data of different fading stages are tested. The SOC estimation error of different fading stages are shown in Fig. 7, Fig.8 and Fig.9, respectively. In the figures, the black solid line indicates the estimation error before SOH correction, and the red dotted line indicates the estimation error after SOH correction. It can be seen that with the decline of the battery, the estimation errors without SOH correction are gradually increased, and the corrected estimation errors are relatively smaller. The SOC estimation based on SOH correction is not only applicable to the SOC estimation of the new battery, but also for the battery after the recession.

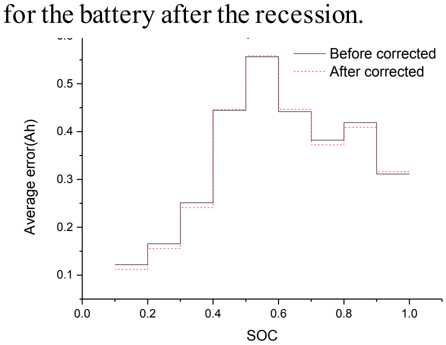

Fig.7 Comparison of error before and after corrected

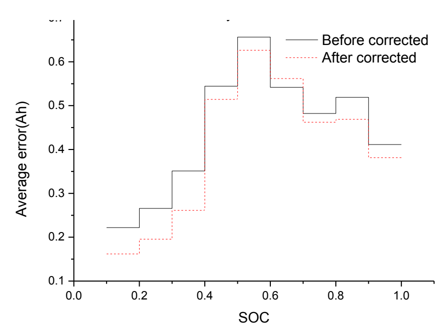

Fig.8 Comparison of error before and after corrected for half decayed battery

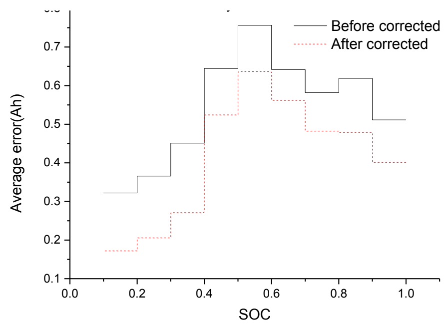

Fig.9 Comparison of error before and after corrected for totally decayed battery

V. Conclusions

In this paper, the battery is tested under the NEDC cycle condition. Based on the detailed analysis of the experimental data, the SOH of the battery is estimated based on Thevenin battery model and BP neural network. Then, the estimated SOH is input to the MEA-BP neural network to estimate the SOC of the battery. The estimation error proved the high accuracy of the method. The application range of SOC estimation method is further broadened not only for the new battery but also for the battery after the recession.

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