State of Health Estimation for Lithium-Ion Batteries Based on Elman Neural Network

Zheng Chen¹, Qiao Xue¹, Yonggang Liu², Jiangwei Shen¹, Renxin Xiao¹
¹Faculty of Transportation Engineering, Kunming University of Science and Technology, Kunming, Yunnan, 650500, China
²State Key Laboratory of Mechanical Transmissions & School of Automotive Engineering, Chongqing University, 400044, China

Abstract

This paper proposes a state of health (SOH) estimation method with integration of grey relational analysis (GRA) with Elman neural network (NN). First, the experimental data of lithium-ion battery life attenuation are analyzed and the health factors (HFs) are extracted. Then, the correlation degree between HFs and SOH are analyzed by the GRA. Finally, the extracted HFs are considered as the model input, and the SOH as taken as a model target output for SOH prediction. The prediction results show that the proposed method has high prediction accuracy that it can be applied to the online SOH estimation.

Keywords: state of health (SOH); health factors (HFs); grey relational analysis (GRA); Elman neural network (NN)

Nomenclature

\[ x_c \] n-dimensional feedback state vector
\[ \omega^1 \] connection weight from the middle layer to the output layer
\[ \omega^2 \] connection weight from input to middle layer
\[ \omega^3 \] connection weight from the context layer to the middle layer
\[ g \] the transfer function of the output neuron
\[ f \] the transfer function of neurons in middle layer

1. Introduction

Due to the predominance of high energy density, long cycle life and low cost, lithium-ion batteries are widely adopted in electric vehicles (EVs) and hybrid electric vehicles (HEVs) [1, 2]. In the actual application, decline of the battery is inevitable, and the operating temperature, different charge and discharge current rates, overcharge, over-discharge and other hazardous usage habits can accelerate the degradation of the battery [3, 4]. In view of these problems, how to evaluate the state of health (SOH) of batteries becomes a critical problem for battery management systems (BMS) in EVs and HEVs.

Currently, there have been a variety of popular algorithms to predict the SOH, which can be mainly divided into three categories [5], i.e., direct measurement method, model-based method, and data-driven method. Due to the long discharge time of the battery and difficulty in covering all kinds of complex environments and working conditions in the actual operation process, the direct measurement method can be used only for offline estimation [6]. The model-based method can well reflect the physical and chemical characteristics of the battery, however the selection of model parameters is largely limited by the accuracy and robustness of the battery model [7]. The data-driven method does not take complex physical and chemical reactions inside the battery into account, but instead directly tracks the battery health information based on the collected actual operation data, by which the SOH estimation can be conducted [8]. Common data-driven methods include neural network (NN) [9], support vector machines (SVM) [10], and Gaussian process regression (GPR) [11].
To accurately and reliably predict the battery SOH, and maintain a moderate amount of calculation and derivation, the health factors (HFs) that have a certain degree of correlation with SOH are extracted. Then the Elman NN is employed to conduct the specific SOH prediction. Finally, all the predicted results are discussed and analyzed to verify the feasibility of the proposed method.

2. The definition of SOH and data analysis

2.1 The definition of SOH

In this paper, the ratio of the remaining available capacity of the battery to the rated capacity is deployed to define SOH, as shown in equ. (1). It is worth noting that the failure threshold of the battery is assumed to be 80% of the rated value [12].

\[
SOH = \frac{C_u}{C_r} \times 100\%
\]  

(1)

where \( C_u \) and \( C_r \) denote the present capacity and the rated capacity of the battery, respectively.

2.2 Heath factors extraction

Two Lithium-ion batteries (referred to as Cell 1 and Cell 2 hereinafter) were selected to conduct the tests. Due to limitation of the variables with the battery data, it is necessary to select the effective health factor from the charging and discharging curves to bridge with the battery SOH [13]. Taking Cell 1 as an example, the charging and discharging curves at partial cycles are shown in Fig. 1 (a) and (b) respectively, in which we can find that the duration of the constant current (CC) charge mode decreases with the cycling operation. We employ \( t_{CC} \) and \( t_{CV} \) to denote the CC charging time and constant voltage (CV) charging time, respectively. Then we can calculate the proportion of CC charging mode as a HF according to equ. (2).

\[
R = \frac{t_{CC}}{t_{CC} + t_{CV}}
\]  

(2)

As shown in Fig 1 (b), In the process of battery discharge, with the increase of cycle times, the voltage decrease rate has obvious change. We choose the equal voltage drop (EVD) as another HF for the SOH estimation as shown in Fig 1 (b) and equ. (3).

\[
EVD = |t_{i1} - t_{i2}|
\]  

(3)

2.3 Grey relational analysis

To better understand the implicit mapping relations, grey relational analysis (GRA) is adopted to analyze the relationship between factors and the SOH. The specific procedure of GRA is introduced in [14]. Figs. 2 and 3 depict the trend of each HF and SOH for Cells 1 and 2, respectively. Table 1 shows the degree value of two batteries. According to Table 1, it shows that these three factors have high relational grade with target SOH.

**Table 1** Grey relational grades between HFs and SOH

<table>
<thead>
<tr>
<th>Battery number</th>
<th>Cycles</th>
<th>R</th>
<th>EVD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cell 1</td>
<td>0.5497</td>
<td>0.9297</td>
<td>0.5587</td>
</tr>
<tr>
<td>Cell 2</td>
<td>0.5503</td>
<td>0.5854</td>
<td>0.7005</td>
</tr>
</tbody>
</table>

**Figure 1** The voltage responses. (a) Charging curves of Cell 1; and (b) Discharging curves of Cell 1.

**Figure 2** Changes of HFs and SOH with cycle numbers for Cell 1.

**Figure 3** Changes of HFs and SOH with cycle numbers for Cell 2.
3. Elman neural network

Elman NN is a kind of dynamic feedback networks, which add a context layer in the hidden layer of the feedforward network as a one-step delay operator to realize the function of memory, so as to facilitate adaption to the time-varying characteristics [15]. The inner structure of the Elman NN is shown in Fig 4.

\[
\begin{align*}
  y(k) &= g(\omega^3 x(k)) \\
  x(k) &= f(\omega^1 x_c(k) + \omega^2 (u(k-1))) \\
  x_c(k) &= x(k-1)
\end{align*}
\]

where \( y \) denotes the m-dimensional output node vector, \( x \) is the n-dimensional mid-layer node element vector, \( u \) represents the r-dimensional input vector, \( x_c \) is the n-dimensional feedback state vector, \( \omega^3 \) expresses the connection weight from the middle layer to the output layer, \( \omega^2 \) means connection weight from input to middle layer, \( \omega^1 \) is connection weight from the context layer to the middle layer, \( g \) illustrates the transfer function of the output neuron, and \( f \) denotes the transfer function of neurons in middle layer.

![Figure 4 Structure of Elman neural network.](image)

From Fig 4, the nonlinear state space function of the Elman NN can be expressed as:

\[
\begin{align*}
  y(k) &= g(\omega^3 x(k)) \\
  x(k) &= f(\omega^1 x_c(k) + \omega^2 (u(k-1))) \\
  x_c(k) &= x(k-1)
\end{align*}
\]

where \( y \) denotes the m-dimensional output node vector, \( x \) is the n-dimensional mid-layer node element vector, \( u \) represents the r-dimensional input vector, \( x_c \) is the n-dimensional feedback state vector, \( \omega^3 \) expresses the connection weight from the middle layer to the output layer, \( \omega^2 \) means connection weight from input to middle layer, \( \omega^1 \) is connection weight from the context layer to the middle layer, \( g \) illustrates the transfer function of the output neuron, and \( f \) denotes the transfer function of neurons in middle layer.

![Figure 5 SOH estimation flowchart.](image)

After the structure of NN is established, partial data of the sample set are inputted for training. Through the GRA, the relational grades between the HFs and SOH are shown in Table 1. It can be seen that the HFs and SOH show a high correlation for two batteries. In this study, we confirm that R, EVD and cycles as input variables of the ENN and SOH as the corresponding output. The network model is trained based on 60% of the sample set data, the parameters of the NN model are fully regulated to make the model prediction with satisfactory precision, and then the remaining sample data are utilized for validation. The detailed flowchart is given in Fig 5 for illustration.

4. Results and discussion

In this paper, the Elman NN is employed to predict and compare the SOH prediction for the two batteries. Figs. 6 to 9 show the prediction results and errors for Cell 1 and Cell 2, respectively. As can be seen from Fig 7, except some individual points where the estimation error is large, the overall estimation error is less than 1%. From Fig 9, it can be observed that the maximum absolute error of SOH of the Cell 2 is 2.29%, however the error scatter is more widely distributed and has a larger oscillation than Cell 1. The capacity of Cell 2 declines rapidly, with SOH dropping below 80% after 125 cycles. From this point of view, the sample of Cell 2 that can be used to train the model is limited. In addition, the features of Cell 2 fluctuate greatly in the later cycle life, leading to a large range of predicted error oscillation. Even so, the estimation result is still in a reasonable error range and the maximum error is less than 2.3%, therefore we can think that the Elman NN model can accurately predict SOH with the HFs extracted properly.

![Figure 6 The results of SOH estimation for Cell 1.](image)

![Figure 7 The error of SOH estimation for Cell 1.](image)
5. Conclusions

In this paper, the Elman NN model is proposed to predict the SOH of the lithium-ion battery based on extracting the health factors. First, the charging and discharging curves are obtained from the experimental data of two lithium-ion batteries, and the proportion of constant current mode and equal voltage drop are extracted as the health factors. Secondly, the grade of correlation between health factors and SOH are analyzed by grey relational analysis to verify that health factors extracted are effective. Finally, the health factors are adopted as the model input and Elman neural network is employed to predict SOH. The prediction results reveal that by extracting reliable health factors, and employing the Elman neural network, accurate and stable SOH prediction results can be attained.

Acknowledgement

This work was supported in part by the National Natural Science Foundation of China (No. 61763021 and No. 51775063), in part by the National Key R&D Program of China (No. 2018YFB0104000), and in part by the EU-funded Marie Sklodowska-Curie Individual Fellowships Project under Grant 845102-HOEMEV-H2020-MSCA-IF-2018.

Reference