State-of-health estimation and remaining useful life prediction of lithium-ion batteries based on extreme learning machine

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Abstract. Lithium-ion batteries have been widely applied in electric vehicles, accurate health state prediction of batteries is one of the key technologies to obtain optimal operation and health management. To achieve the highly accurate state of health (SOH) estimation and remaining useful life (RUL) prediction, a framework based on extreme learning machine (ELM) is proposed. Firstly, the indirect health indicators are extracted from discharge data. Then, the ELM model is proposed to estimate SOH and predict RUL. Finally, the propagation neural network based on particle swarm optimization (BPNN-PSO) is compared with the ELM method. The results show that proposed method hits lower average root mean square error for SOH and RUL.

1. Introduction

With the increasingly fossil fuels shortage and serious environmental problems, the electric vehicles (EVs) have been gained widely attention. The lithium-ion batteries are widely used in vehicle industries owing to the no memory effect, superior life cycle, and safety [1]. However, the capacity fades with the increase of charging (discharging) cycles because of the different degradation mechanisms. This phenomenon not only weakens the range of EVs but also causes safety phenomenon. Therefore, the accurate SOH estimation and RUL prediction are the basic prerequisite to ensure safety and effectiveness of EVs.

The SOH estimation and RUL prediction of the batteries are the core component of the battery management system (BMS) [2-3]. Although the direct health indicators are widely applied, these indicators are difficult to obtain. A growing number of researchers focused on the indirect health indicators [4]. The voltage, current and temperature is considered as indirect health indicators. The discharge voltage cut-off interval and discharge constant current interval is selected based on the actual working conditions of EVs.

Currently, existing methods for SOH estimation can be divided into two categories: the model-based methods and the data-driven methods. The model-based methods are focus on the relation of capacity degradation trend, such as, empirical method and equivalent circuit model (ECM) [5]. However, the accurate battery model is difficult to establish. The data-based method has been widely used for SOH estimation and RUL prediction over the past decades, such as the logistic regression (LR), deep learning (DL), artificial neural networks (ANNs), etc. [6-7]. However, the traditional feed forward neural network adopts the gradient descent method, which performs slow training speed and fall into local minimum phenomenon. Extreme learning machine (ELM) can address the problem of difficult battery model and slow training speed. ELM randomly generates the connection weights and
the thresholds during the training process, which can obtain the fast training speed and better generalization performance. Therefore, the ELM is proposed for SOH estimation and RUL prediction.

2. Extraction of indirect health indicators

The Battery Data Set (NASA PCoE Research Center) is used in this paper. At 24°C, the discharging and charging of 18650 lithium-ion batteries (B5, B6, B7) is selected. The battery's threshold is 1.38Ah [8]. The capacity fade of each battery is shown in the Figure 1. It can be obtained that the trend of capacity fade is complex and nonlinear. The state of health is shown in the Figure 2.

![Figure 1. The capacity fade of each battery.](image1)

Although the accurate SOH estimation and RUL prediction can be obtained by direct health indicators, the direct health indicators are difficult to obtain from online measurements. Therefore, the extraction of indirect health indicators is used for SOH estimation and RUL prediction. The discharge voltage cut-off interval (DVCI) and discharge constant current interval (DCCI) is used as the indirect health indicators. Then, the gray relation analysis is proposed to analyse the relation between the SOH (RUL) and capacity. The DVCI and DCCI is analysed with gay relational analysis. Under the battery NO.5, the relation between the DVCI (DCCI) and capacity is 0.889 (0.898). Therefore, the DVCI and DCCI as indirect health indicators can be used SOH and RUL for lithium-ion batteries.

3. Method of extreme learning machine

The ELM is suitable for prediction problems of complex nonlinear systems. The ELM has three-layer structure, which is composed of the input layer, the hidden layer and the output layer. The connection weight between the input layer and the hidden layer is randomly generated during training process. The ELM structure is shown in Figure 3.

![Figure 2. The state of health of each battery.](image2)

The connection weights of the hidden layer and the input layer (the output layer) are respectively as \(\omega = [\omega_1, \omega_2, \ldots, \omega_m]^T\) and \(\beta = [\beta_1, \beta_2, \ldots, \beta_m]^T\). The threshold of hidden layer neurons is set as \(b = [b_1, b_2, \ldots, b_l]^T\). The input data and the training data are set respectively as \(X = [X_1, X_2, \ldots, X_p]^T\) and \(Y = [Y_1, Y_2, \ldots, Y_q]^T\). The \(f(x)\) is the activation function of the hidden layer. According to the structure diagram of the ELM model, the output of the network is \(T = [t_1, t_2, \ldots, t_o, t_o,x\ldots o]^T\).
Figure 3. Structure of the extreme learning machine.

\[ t_j = \begin{bmatrix} t_{j1} \\ t_{j2} \\ \vdots \\ t_{jn} \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{l} \beta_{ij} f(\omega_{ij}) \\ \sum_{i=1}^{l} \beta_{ij} f(\omega_{ij}) \\ \vdots \\ \sum_{i=1}^{l} \beta_{ij} f(\omega_{ij}) \end{bmatrix} \quad (j=1,2,\ldots,Q) \quad (1) \]

\[ H\beta = T \]

\[ H(\omega_1, \omega_2, \ldots, \omega_l, b_1, b_2, \ldots, b_n) = \begin{bmatrix} f(\omega_{11} + b_1) & f(\omega_{12} + b_1) & \cdots & f(\omega_{1n} + b_1) \\
 f(\omega_{21} + b_2) & f(\omega_{22} + b_2) & \cdots & f(\omega_{2n} + b_2) \\
 \vdots & \vdots & \ddots & \vdots \\
 f(\omega_{l1} + b_1) & f(\omega_{l2} + b_1) & \cdots & f(\omega_{ln} + b_1) \end{bmatrix} \quad (3) \]

Where, \( \omega_j = [\omega_{j1}, \omega_{j2}, \ldots, \omega_{jn}] \) and \( x_j = [x_{j1}, x_{j2}, \ldots, x_{jn}]^T \). In order to obtain the accurate SOH estimation and RUL prediction, the model of extreme learning machine is proposed. The structure of ELM is shown in Figure 4.

4. Results and discussion

4.1. SOH estimation

The accuracy of SOH estimation is of great importance to the operational safety of electric vehicles. In this study, The SOH is determined by normalized capacity as follows:

\[ SOH = \frac{\text{actual capacity}}{\text{rated capacity}} \quad (4) \]

The NO.5, NO.6, and NO.7 from the NASA PCoE is analysed to verify the ELM method. The voltage, current and capacity are used to as training data and testing data. Then, the training data includes 112 samples and the test data includes 56 samples. The results and errors of the ELM method are shown in Figure 5. From the Figure 5, we can discern that ELM method has the higher accuracy SOH estimation.
Figure 4. Schematic diagram of the ELM for SOH estimation and RUL prediction.
4.2. RUL prediction

For the NO.5 battery, the 59th cycles, 59th cycles, and 99th cycles are used as training data, and the following cycles are used as prediction data. The prediction results and errors are shown in Figure 6. When the training samples are reduced, the good RUL prediction results are obtained. However, as the training cycles decrease, the prediction errors gradually increase.

The 99th cycles are used as training data, and the following 69 cycles are used as prediction data. Then, the BPNN-PSO is compared to further verify the effectiveness of the proposed method. The RUL prediction results of the ELM method are shown in Figure 7. The trend of capacity is a dynamic and nonlinear degeneration owing to the external disturbances and different degradation mechanisms. From the Figure 7, although the traditional BPNN-PSO can obtain good prediction results, the prediction error is large and the RUL prediction fluctuates greatly.

To further clarify the prediction performance of the proposed method, the prediction performance is presented in Table 1. As shown in Table 1, the RMSE, MAE, and MAPE are 3.01%, 2.33%, and
1.74%, respectively, under the batteries NO.5. Under the batteries NO.6, the RMSE, MAE, and MAPE of the BPNN-PSO are 3.35%, 2.62%, and 2.01%, respectively. The RMSE, MAE, and MAPE are 3.01%, 2.33%, and 1.74%, respectively, under the batteries NO.7. In the proposed ELM model, the RMSE under the batteries NO.5, NO.6, and NO.7 are 1.29%, 1.98%, and 1.81% MAE is 1.01%,1.38%, and 1.47% and MAPE is 0.76%,1.06%, and 1.00%, respectively. All prediction indicators of RUL prediction of ELM are low 2%.

![Graphs showing RUL prediction for batteries NO.5, NO.6, and NO.7](image)

**Figure 7.** Results of lithium-ion batteries for RUL prediction: (a) RUL prediction with the NO.5 battery, (b) RUL prediction with the NO.6 battery, (c) RUL prediction with the NO.7 battery.

| Methods | Numbers | RMSE (%) | MAE (%) | MAPE (%) |
|---------|---------|----------|---------|----------|
| BPNN-PSO | NO.5    | 3.01     | 2.33    | 1.74     |
|          | NO.6    | 3.35     | 2.62    | 2.01     |
|          | NO.7    | 2.78     | 2.42    | 1.65     |
|          | NO.5    | 1.29     | 1.01    | 0.76     |
| ELM     | NO.6    | 1.98     | 1.38    | 1.06     |
|          | NO.7    | 1.81     | 1.47    | 1.00     |

**Table 1.** Prediction performance of tested methods.
5. Conclusions
To obtain the highly accurate SOH estimation and RUL prediction, the ELM is proposed. Firstly, the indirect health indicators are proposed from discharge data. The discharge voltage cut-off interval and discharge constant current interval is analysed with gay relational analysis. Then, the ELM is proposed to improve the SOH estimation and RUL prediction. Finally, the ELM is compared with traditional BPNN-PSO, which verify the superiority of the ELM model. The results show that all the prediction indicators are low 2%.

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