Residual Life Prediction of Lithium Battery Based on Small Sample Data Sets

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Abstract. In the recycling process of lithium-ion battery, the poor external environment will lead to the degradation of battery performance, so it is necessary to predict the residual life of lithium-ion battery. However, the aging cycle of lithium-ion battery is long, so it is difficult to obtain sufficient aging data in a short time. Aiming at the problem of low prediction accuracy of lithium battery residual life under the condition of small samples, a BP neural network modelling algorithm fused with expert knowledge is proposed. Firstly, indirect health factors were extracted from the aging data of lithium battery in NASA PCOE laboratory. Secondly, the initial weight and threshold of BP neural network were optimized by genetic algorithm, and the initial multiplier value of the augmented Lagrange function was set according to Spearman correlation coefficient. Finally, the expert knowledge is integrated into the training process of BP neural network through the augmented Lagrange multiplier method. Simulation results show that the proposed algorithm has higher prediction accuracy than the traditional BP neural network under the condition of small samples.

1. Introduction
As a carrier of electric energy storage and conversion, lithium-ion battery has the advantages of high specific energy, high working voltage, wide temperature range, low self-discharge rate, long cycle life and good safety[1]. However, in the recycling process of lithium-ion battery, due to aging diaphragm, high temperature, improper use and bad external environment, the activity of the battery will be reduced, resulting in the performance degradation of electrical equipment and equipment failure. Therefore, it is necessary to carry out the residual life prediction of lithium-ion battery. The data-driven modeling method can directly establish the residual life estimation model of the battery based on the aging data of the battery life, but the data-driven modeling method needs sufficient training samples, and the aging cycle of lithium-ion battery is long, so it is difficult to obtain sufficient aging data in a short time.

The prediction of the residual life of lithium-ion battery under the condition of small samples has attracted extensive attention of scholars at home and abroad. In reference [2], an overall trend diffusion technique is proposed to generate virtual samples, which effectively expands the sample space [2]. In reference [3], bootstrap method and kernel density Latin hypercube sampling method are used to expand training samples respectively, and the problem of BP neural network modeling for small sample data sets is solved under the condition of ensuring the self-rule of small sample data sets [3]. In reference [4], expert knowledge is integrated into the training process of neural network in the form of penalty term by using derivative constraint method [4]. In reference [5], the prediction problem under the condition of small sample is solved by combining the improved particle swarm optimization algorithm with BP neural...
network[5]. In reference [6], the training accuracy of small sample BP neural network is improved by designing residual BP neural network and stacking multiple modules.

At present, there are two methods to predict the residual life of lithium-ion battery under the condition of small sample. One is the method of expanding data to obtain the same distribution rule as the small sample data; The other is the combination of expert knowledge and neural network. The augmented lagrange multiplier method provides a unified framework for different types of constraints. In this paper, BP neural network is selected for modeling. Firstly, the expert knowledge is integrated into the training process of BP neural network through the augmented lagrange multiplier method to improve the prediction accuracy of BP neural network under the condition of small samples. At the same time, the optimal initial weights and thresholds are obtained by genetic algorithm, and the initial multiplier value of augmented Lagrange function is set according to the Spearman correlation coefficient.

2. Extraction and analysis of indirect health factors
In this paper, the capacity is selected as the direct health index, and the indirect health factors are extracted by using the NASA data set # 5 battery.

2.1 Extraction of indirect health factors.
As shown in Figure 1, according to different cycle voltage and current curves in charging process, the time interval characteristics of charging phase are extracted. F1: equal voltage rise charging time interval, that is, the time that the voltage rises from a lower value to a higher value in CC charging process; F2: equal current drop charging time interval, the time that the current drops from a higher value to a lower value during CV charging.

As shown in Figure 2, the third indirect health factor (F3) is the equal voltage drop discharge time interval extracted from the discharge voltage curve by analogy with F1 and F2.

![Figure 1. Charging voltage and current curves of battery # 5 in six charging cycles](image)

![Figure 2. Discharge voltage curves and F3 extraction in the six discharge cycles of battery](image)
Temperature feature extraction, F4: the average temperature of the battery between the start time of F1 and the end time of F2. F5: average temperature of battery in F3 period.

The Spearman correlation coefficient was calculated as follows

$$\rho = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 \sum_{i=1}^{n} (y_i - \bar{y})^2}}$$ (1)

The following table shows the correlation coefficient values between the above five indirect health factors and capacity.

| Indirect health factors | F1    | F2    | F3    | F4    | F5    |
|-------------------------|-------|-------|-------|-------|-------|
| Pearson coefficient     | 0.8632| 0.8664| 0.9870| 0.9365| 0.7868|

3. Genetic Algorithm

The specific implementation steps of genetic algorithm are as follows:

(1) Data normalization: the first step is to normalize the input data. Equation (2) is the data normalization formula.

$$x_i = \frac{x_i - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}$$ (2)

(2) Chromosome coding: chromosome coding refers to writing input data in binary form.

(3) Population initialization: after binary encoding of input data, a group of data is randomly generated.

(4) Evaluation of fitness function:

$$F = k \left( \sum_{i=1}^{n} \text{abs}(y_i - o_i) \right)$$ (3)

(5) Genetic operation: in this paper, roulette is used to select individuals.

(6) If the termination condition is reached, the result will be output; otherwise, go back to step (3) and operate again until the condition is met.

4. Acquisition and expression of expert knowledge

Firstly, the output formula of each neuron in the output layer of BP neural network is as follows:

$$o_k = g(\text{net}_k - b_k)$$ (4)

As shown in Figure 3, indirect health factors F1 and F3 are monotonically increasing with output capacity.

According to the output formula of (4) BP neural network, the mathematical expression formula of expert knowledge can be obtained by derivation

$$\frac{\partial O_k}{\partial x_l} = \frac{\partial O_k}{\partial H_l} \frac{\partial H_l}{\partial n_l} \frac{\partial n_l}{\partial x_l} = \sum_{m=1}^{W_{km}} (W_{km} \cdot f(n_i) \cdot W_{ik})$$ (5)
5. BP neural network based on Augmented Lagrange multiplier method

In this paper, expert knowledge is taken as the constraint condition, and the augmented Lagrange function is taken as the objective function of BP neural network. As shown in the following, the generalized Lagrange multiplier method is used to deal with constrained optimization problems.

\[
\begin{aligned}
\text{min} & \quad E = \sum_{p=1}^{P} \frac{1}{2} [Y_p - f(X_p)]^2 = \sum_{i=1}^{I} \frac{1}{2} e_i^2 \\
\text{s.t.} & \quad g_i(w, v, b^{(1)}, b^{(2)}) = \frac{\delta f(X_i)}{\delta x_i} > 0 \quad i = 1, 2, \ldots, I
\end{aligned}
\]  

(6)

Firstly, the inequality constrained optimization problem is replaced by the following equality constrained optimization problem

\[
\begin{aligned}
\text{min} & \quad E = \sum_{p=1}^{P} \frac{1}{2} [Y_p - f(X_p)]^2 = \sum_{i=1}^{I} \frac{1}{2} e_i^2 \\
\text{s.t.} & \quad g_i(w, v, b^{(1)}, b^{(2)}) - z^2 = 0
\end{aligned}
\]  

(7)

According to the above constrained optimization problem, the augmented Lagrange function is constructed as follows:

\[
\psi(w, v, b^{(1)}, b^{(2)}, \lambda, \mu) = \frac{1}{2} \sum_{i=1}^{I} e_i^2 - \lambda [g_i(w, v, b^{(1)}, b^{(2)}) - z^2] + \mu \left[ g_i(w, v, b^{(1)}, b^{(2)}) - z^2 \right]^2
\]  

(8)

By finding the first derivative of \( \psi \) with respect to \( Z \), the auxiliary variable \( Z \) is eliminated. Thus

\[
\psi = \sum_{i=1}^{I} e_i^2 + \frac{1}{2\mu} \left[ \min(0, \mu g(-\lambda^2)) \right]^2 - \lambda^2
\]  

(9)

(1) When the output of BP neural network satisfies expert knowledge, the updating process of weight and threshold is as follows:

\[
\frac{\partial E}{\partial W} = e_iH_i + a(1-H_i)H_iW^i
\]  

(10)

\[
\frac{\partial E}{\partial B} = e_i
\]  

(11)

\[
\frac{\partial E}{\partial W'} = W^2(1-H_i)H_i e_i x_i
\]  

(12)

\[
\frac{\partial E}{\partial B'} = W^2(1-H_i)H_i e_i
\]  

(13)

(2) When the output of BP neural network does not meet the requirements of expert knowledge, the updating process of weight and threshold is as follows:

\[
\frac{\partial E}{\partial W} = e_iH_i + a(1-H_i)H_iW^i
\]  

(14)

\[
\frac{\partial E}{\partial B} = e_i + a
\]  

(15)

\[
\frac{\partial E}{\partial W'} = W^2(1-H_i)H_i e_i x_i + a(1-H_i)H_i W^2(W_i x_i - 2H_i W^i x_i + 1)
\]  

(16)

\[
\frac{\partial E}{\partial B'} = W^2(1-H_i)H_i e_i + a(1-H_i)H_i W^2(1-2H_i)W^i
\]  

(17)

6. Algorithm flow

To sum up, the steps of BP neural network algorithm based on genetic algorithm and Lagrange multiplier method are as follows:
Figure 4. algorithm flow chart

Step 1: determine the initial value. Given the initial weights and thresholds of neural network parameters, the initial multiplier value is set according to Spearman correlation coefficient \( \lambda(0) \geq 0 \), initial value of penalty function \( \mu(0) \geq 0 \), termination conditions \( \beta(0) \), maximum training times \( \text{Train Max} \), renewal factor \( 0 < \gamma \leq 1 \), \( \delta > 1 \), total number of iterations \( \text{Iterate Max} \), let \( k = 1 \);

Step 2: update the weight threshold according to formula (14) ~ (21)

Step 3: test termination conditions. If \( \beta(k) \leq \epsilon \) or \( k \geq \text{Iterate Max} \), stop iteration;

Step 4: update the penalty function. If \( \beta(k) \geq \gamma \beta(k-1) \), then \( \mu(k+1) = \delta \mu(k) \); else \( \mu(k+1) = \delta \mu(k) \);

Step 5: Let \( k = k + 1 \), turn to step (2).

According to the multiplier method, the renewal formula of termination conditions \( \lambda(k) \) and \( \beta(k) \) is as follows:

\[
\beta(k) = \sum_{i=1}^{l} \min \left[ g(w_i, v_i, b_i, h_i), \frac{\lambda_i(k)}{\mu} \right] i = 1, 2, \ldots, l
\]

\[
\dot{\lambda}_i(k+1) = \begin{cases} 
\dot{\lambda}_i(k) - \mu g_i(w_i, v_i, b_i) & \text{if } \mu g_i(w_i, v_i, b_i) - \dot{\lambda}_i(k) \leq 0 \\
0 & \text{if } \mu g_i(w_i, v_i, b_i) - \dot{\lambda}_i(k) > 0 
\end{cases}
\]

7. Simulation result

According to the above steps, the two pieces of expert knowledge in the third section of this paper are integrated into the training process of BP neural network. The initial weights and thresholds in this paper are obtained by the genetic algorithm in the second section; the learning rate was set to 0.001; the initial value of penalty function is 20; the threshold is 0.00001; the termination condition is 10; the maximum number of training is 10000; the total number of iterations is 100; the five health factor data sequences in Section 1 are extracted. The number of neural network training sets is set to 20, and the number of test sets is set to 148; According to the Spearman correlation coefficients of F1 and F3, the correlation coefficient between F3 and capacity is stronger. Set the initial multipliers to \( c_1 = c_2 = 0.5 \) and \( c_1 = 0.5 \) \( c_2 = 0.8 \) to compare. The average error is used as the network evaluation index. The following...
Figure 6 shows the comparison of the training results of BP neural network based on genetic algorithm and augmented Lagrange multiplier with different initial multiplier values.

It can be seen from the above figure that the BP neural network based on genetic algorithm and augmented Lagrange multiplier method can effectively improve the prediction accuracy in predicting the residual life of lithium-ion battery under the condition of small samples. And through the Spearman correlation coefficient to improve the augmented Lagrange multiplier method, the final prediction results are also improved.

8. Conclusions
This paper first optimizes the initial weights and thresholds of BP neural network based on genetic algorithm, and then integrates expert knowledge into the training process of BP neural network through augmented Lagrange multiplier method. Aiming at the problem that the initial multiplier of augmented Lagrange multiplier method is difficult to determine, it is set according to Spearman correlation coefficient. In this paper, BP neural network based on genetic algorithm and improved augmented Lagrange multiplier method is used to solve the problem of low prediction accuracy of lithium battery residual life under the condition of small samples.

The limitations of this study are: (1) only monotonic prior knowledge is obtained; (2) Only NASA lithium battery aging data set is used to verify the algorithm. In the future, we will integrate more types of expert.

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