Cycle Life Prediction of Lithium Batteries Based on Generalized Regression Network with Improved PSO

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Abstract. To predict the cycle life of lithium-ion batteries more accurately, an improved PSO algorithm and a generalized regression neural network (GRNN) combined with the cycle life prediction method of lithium ion battery are proposed. Based on the simulation and actual prediction data, the results show that the established model has higher prediction accuracy than GRNN, which is of great significance for solving the life prediction accuracy of lithium iron phosphate battery.

1. Introduction
Lithium-ion batteries are widely used in the electric vehicle industry, but the accurate prediction of the cycle life of batteries has always been a difficult and urgent problem in battery management technology. At this stage, the methods commonly used to predict battery cycle life are as follows \cite{1-3}: Prediction method based on physical failure model \cite{4}, Prediction method based on characteristic parameters \cite{5} and data-driven prediction which can accurately predict the cycle life of commercial lithium iron phosphate batteries using only early cycle data without analyzing the battery decay mechanism \cite{6}.

This paper uses a data-driven method to predict cycle life. Fully consider the key factors affecting the cycle life and obtain the optimized parameters of the battery discharge as input parameters of the network model through experimental data, the generalized Regression Neural Network Model was established. This model achieves a more accurate prediction of cycle life, and improves the prediction accuracy compared with the single BP neural network and the prediction results obtained by GRNN.

2. Construction of battery cycle life prediction model
The particle swarm optimization (PSO) algorithm first initializes a group of particles in the feasible solution space, and each particle represents a potential optimal solution to the extreme value optimization problem. The particle moves in the solution space, and the individual position is updated by tracking the individual extremum Pbest and the group extremum Gbest. The fitness value is calculated every time the particle is updated, and the fitness value of the new particle is compared with the individual extremum and the group extremum. During each iteration, the particles update their speed and position through individual extremum and group extremum. The formula is updated as follows:
The inertia weight \(\omega\) in the equation reflects the ability of the particle to inherit the previous velocity. The larger \(\omega\) is favorable for local search, while the smaller \(\omega\) is more conducive to global search. To balance the global and local search capabilities of the algorithm, this paper uses linear time-varying acceleration constants, including high cognitive constraints \(C_1\) max and low social constants \(C_2\) min, \(T_{\text{max}}\) is the maximum number of iterations, while considering a sine time-varying \(\omega\):

\[
\omega(i) = \omega_{\text{max}} + (\omega_{\text{min}} - \omega_{\text{max}}) \cos \left( \frac{\theta}{T_{\text{max}}} \right), \quad \theta = \frac{T - \frac{T_{\text{max}}}{2}}{T_{\text{max}}} \tag{5}
\]

Equations (3) and (4) describe the linear modulation of acceleration, and equation (5) gives the modulation of the truncated sine function of the inertia weight. Compared with the traditional linear modulation, this method can observe that the high-speed particle inertia component in the early half of the search is beneficial to global search and find a superior region; in the lower half of the search, the speed of inertia facilitates local search in superior areas is lower, save the whole algorithm running time.

3. Improved PSO-GRNN algorithm for cyclic life prediction

3.1. Acquisition of training samples

In this paper, three 18650 lithium batteries numbered 1, 2, and 3 were selected for experiments. In this experiment, to speed up the battery aging process, charging at 1.5C rate, discharging at 2C rate, and reducing the discharge cut-off voltage method were used. Two groups of data were selected for network training modeling, and one group was used for predictive verification of battery cycle life. The data selected in this paper is used to predict the life when the battery capacity drops to about 80%. The selected training data can be seen from Fig. 1, where # 1 and # 2 are the two batteries selected respectively. The input parameters of the network include the battery’s charge cut-off voltage, discharge terminal voltage and battery internal resistance. The output is the actual capacity after the battery is cycled, and the increase in the number of cycles corresponds to the attenuation of the battery capacity. As the cycle increases, the time to reach the cutoff voltage also changes. The trend of the cutoff voltage of a battery is shown in Fig. 2. It can be seen from the figure that as the cycle increases, the time to reach the cutoff voltage is advanced. It reflects that the battery capacity is declining.
3.2. Hybrid estimation algorithm setting

The steps which use improved particle swarm optimization algorithm PSO to optimize the GRNN network to predict the battery cycle life value are:

1. Initialize the basic parameters, set the population size of the particle S, the maximum number of iterations Mg, the initial position x0, and the particle swarm size SP.

2. According to the initial position and velocity of the particle generated from step (1), optimize the particle position calculation and increase the calculation speed by linear modulation of acceleration

3. Integrate the constraint condition with the fitness function and calculate the fitness value.

4. Search the global optimal fitness value from the particle swarm to minimize the error.

5. Check the conditions of the exit procedure, either to reach the maximum number of iterations or to meet the set convergence accuracy. If it is satisfied, the optimal result is output.

6. Update the speed and position of the particle based on the current global fitness value and individual fitness value.

7. Update the fitness value under the new position of the particle.

8. Repeat steps (4)-(7) until the exit condition is met.

Figure 1. Capacity degradation routes along with increased cycles of battery 1# and 2#.

Figure 2. Discharge cutoff voltage in battery cycle.

3.3. Forecast results and analysis

Using the battery data obtained by the battery test platform, the standardized sample data is input into the improved PSO-GRNN algorithm network model using MATLAB. The network model estimation
results and estimation accuracy are shown in Fig. 4 and Fig. 5. It can be seen from Fig. 5 that the improved PSO-GRNN algorithm is used to estimate the battery cycle life accuracy, and the maximum estimation error does not exceed ±3%, indicating that the algorithm is accurate.

Figure 4. Battery cycle life prediction curve based on PSO-GRNN algorithm

Figure 5. Battery cycle life estimation error curve based on PSO-GRNN algorithm.

Through the previously trained PSO-GRNN neural network, the experimental data is input for verification. The actual cycle life error corresponding to different algorithms is shown in Fig. 6. To verify the validity of the proposed model, three performance indicators are used to evaluate the effectiveness of the model, including mean absolute error (MAE), root mean square error (RMSE), and mean absolute error percentage (MAPE).

The prediction results of the various algorithms obtained according to the formula are shown in Table 1. The MAE calculates the average of the absolute values of the deviations of all individual observations from the arithmetic mean. The smaller the value, the higher the prediction accuracy. The RMSE calculates the square root of the deviation between the prediction value and the true value and the square root of the Predicted sample number n. The smaller the value, the higher the measurement accuracy. The coefficient of determination R2 is a comprehensive measure of the degree of fit to the regression model. The larger the coefficient of determination, the higher the degree of model fit.

It can be seen from the data in Table 1 that the improved PSO-GRNN proposed in this paper has higher prediction accuracy and better fitting degree than PSO-GRNN, GRNN, BP and GA-BP, which has obvious advantages. The error of this model algorithm is controlled within ±3%, and the validity and accuracy of the algorithm are proved again.

Figure 6. Comparison of battery cycle life estimation error based on different algorithms.
Table 1. Error comparison based on different algorithms.

| Algorithm   | MAE      | RMSE     | MAPE   | R²       |
|-------------|----------|----------|--------|----------|
| PSO-GRNN    | 0.000948419 | 0.003893763 | 0.000548988 | 0.99899615 |
| GRNN        | 0.017266341 | 0.020181652 | 0.01004494  | 0.97596212 |
| BP          | 0.028152079 | 0.037499564 | 0.015971947 | 0.96165029 |
| GA-BP       | 0.017825   | 0.021701  | 0.004365  | 0.99197269 |

4. Summary
In this paper, the improved particle swarm optimization algorithm is used to optimize the parameters of GRNN network. The search mechanism of acceleration inertia weight is introduced in the optimization process to improve the PSO algorithm, and the ability and convergence speed of PSO algorithm in global and local optimization are improved. Finally, the simulation results of experimental data show that compared with BP and GRNN network models, the improved PSO-GRNN network model used in this paper has higher network learning efficiency and cycle life efficiency and cycle life estimation accuracy.

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References
[1] REZVANI M, ABUALI M, LEE S, et al. A comparative analysis of techniques for electric vehicle battery Prognostics and Health Management (PHM) [J]. SAE Technical Paper, 2011 (191): 1-9.
[2] GU W J, SUN Z C, WEI X Z, et al. A new method of accelerated life testing based on the Grey System Theory for a model-based lithium-ion battery life evaluation system [J]. Journal of Power Sources, 2014 (267): 1-9.
[3] Zhu Liangbiao. Data Driven Lithium Ion Battery Remaining Life Prediction Model and Software Implementation [D]. Guangzhou: South China University of Technology, 2014.
[4] Q Zhang, R E White. Capacity fade analysis of a lithiumion cell [J]. Journal of Power Sources, 2008, 179 (2): 793-798.
[5] Andre D, Meiler M, Steiner K, et al. Characterization of high-power lithium-ion batteries by electrochemical impedance spectroscopy. I. Experimental investigation [J]. Journal of Power Sources, 2011, 196 (12): 5334-5341.
[6] Severson K A, Attia P M, Jin N, et al. Data-driven prediction of battery cycle life before capacity degradation [J]. Nature Energy, 2019, 4 (5): 383.