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AFSA-ELM Based Prediction of the Remaining Useful Life of Lithium Batteries

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Abstract: *It is of great significance to accurately determine the health status of lithium-ion batteries. To address the problem that the prediction of a single limit learning machine algorithm is prone to jumping, the method of using artificial fish swarm optimization to optimize the limit learning machine is proposed to try its best to predict the model of the remaining life of lithium-ion batteries. Firstly, the isovoltage discharge time is extracted as an indirect health factor, then the limit learning machine is optimised using the artificial fish swarm algorithm to build an indirect prediction model for the remaining life of Li-ion batteries, and finally a validation evaluation is carried out based on the NASA dataset B0005-B0006. The experimental results show that the proposed model predicts stable prediction results with high accuracy and small error in prediction results.*

Keywords: *Lithium-ion batteries; Artificial fish swarming algorithms; Extreme learning machines; Remaining useful life.*

1. Introduction

Lithium-ion batteries because of the advantages of high specific energy, stable discharge performance, good environmental adaptation performance, is widely used in the military as well as with aspects, at present, lithium-ion batteries gradually replaced the lead battery, based on lithium batteries, the development of new energy vehicles, electric vehicles also changed to lithium batteries[1-3]. Widely used lithium batteries will bring safety problems, according to the previous generation of relevant research, lithium battery capacity decay to 80% of the initial capacity, it has a greater possibility of failure such as bursting into flames, resulting in the loss of personnel and property.

In order to reduce risk and provide early warning, scholars at home and abroad have conducted research on the remaining life of lithium-ion batteries, and the main research methods are data-driven and physical modeling approaches[4]. The physical model-based approach requires researchers to fully understand the chemical discharge mechanism of the battery, and the model needs to be reconstructed for different lithium batteries, so the applicable performance is poor. For this reason, the data-driven approach has emerged, i.e. constructing predictive health factors through the historical data of battery operation, such as voltage, current, capacity, etc., to obtain the battery-related decay status, so as to obtain the remaining battery life, mainly including The indirect prediction is suitable for simple health factor extraction, while the direct prediction is suitable for complex operating conditions, which is the mainstream research direction at present. Tipping M E et al. proposed the use of support vector machines for remaining life prediction[5]. Ali J et al. proposed the use of a genetic algorithm improved limit learning machine for remaining life prediction of lithium-ion batteries[6]. From the prediction results, each prediction method is more advanced and has higher prediction accuracy, but the training time of the prediction model is long. Therefore, Jiang Yuanyuan et al. proposed to use the limit learning machine method to build an indirect prediction model for the remaining life of the battery for problems such as long prediction of the remaining use of the lithium battery directly, but the standard ELM model will produce jumps in the prediction results due to its random input weights, so optimization is needed to ensure prediction results are reliable.

The idea of the article is: firstly, to build a Li-ion battery remaining life prediction model through an artificial fish swarm algorithm algorithm to optimise the limit learning machine, then, to build an indirect health factor for Li-ion battery remaining life prediction by extracting the isovoltage discharge time, and finally, to validate and evaluate the model using the NASA battery dataset, and to concludeAs your paper will be an important component in the journal, we highly recommend that all the authors follow this

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2. Indirect Health Factor Construction

The selection of appropriate lithium-ion battery operating parameters as an indirect health factor will directly affect the accuracy of remaining life prediction and the applicability of the prediction model. The indirect health factor was determined by calculating the correlation between battery capacity degradation and the parameters of battery operation. It was found that the time elapsed from a low voltage to a relatively high voltage during the charging process of a Li-ion battery is consistent with the trend of capacity degradation of the battery during the cycling process. Therefore, this paper uses the equal voltage drop discharge time as an indirect health factor for the prediction of RUL of Li-ion batteries. During each discharge cycle, the time when the battery is at low and high voltage is extracted and the difference is calculated as the equal voltage drop discharge time. The calculation expression is as follows.

$$\Delta T_i = | T_i^l - T_i^h |, \qquad i = 1, 2, 3, \ldots, n \tag{1}$$

Where, ΔT is the equal voltage drop discharge time, T_i^l is the moment corresponding to the second cycle low voltage, T_i^h is the moment corresponding to the second cycle high voltage and n is the maximum number of cycles of the lithium battery. Therefore, the equal voltage drop discharge time series can be expressed as:

$$t_{HI} = \{\Delta T_1, \Delta T_2, \Delta T_3, \ldots \Delta T_n\} \tag{2}$$

3. Construction of a Residual Life Prediction Model for Lithium-ion Batteries

3.1. Extreme Learning Machine Overview

Extreme learning machine is a learning algorithm of single hidden layer feedforward neural network, which is widely used in the prediction of health status because of its simple model and strong learning ability [7], however, because its input weights and thresholds are given randomly during training and prediction, which leads to fluctuations in the output and unreliable prediction results, so, for this problem, it is proposed to optimize ELM using gravitational search algorithm to obtain more stable and reliable prediction results[7].

The structure of ELM algorithm consists of 3 layers, which are input layer, implicit layer and output layer, and its structure is shown in Figure1.

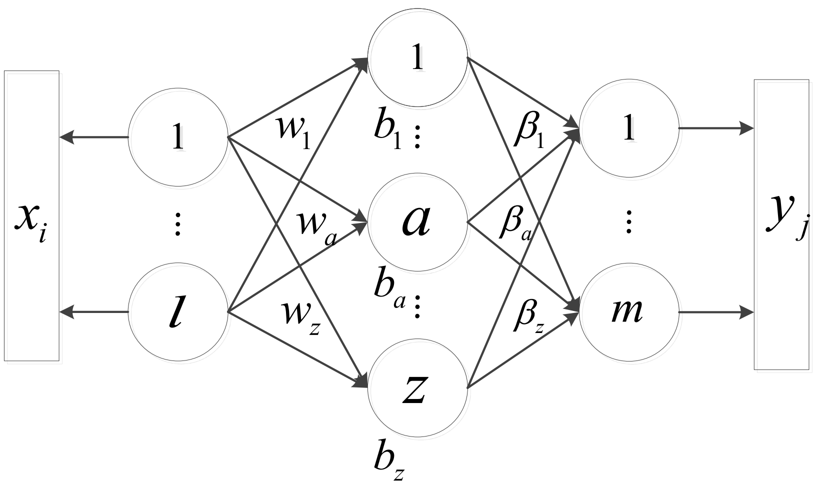

Fig. 1: Algorithm structure of extreme learning machine

According to the structure diagram, the ELM algorithm can be described as follows[7].

$$y_j = \sum_{i=1}^{N} \beta_i g(x_i) = \sum_{i=1}^{l} \beta_i g(w_i \cdot x_i + b_i) \quad j = 1, \ldots, m \tag{3}$$

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Among them. $x_i = [x_{i1}, x_{i2}, ..., x_{il}]^T \in R^l$, $y_j = [y_{j1}, y_{j2}, ..., y_{jm}]^T \in R^m$, $w_i = [w_{i1}, w_{i1}, ..., w_{il}]^T$, which are the weights from the input layer to the implied layer. $\beta_i = [\beta_{i1}, \beta_{i1}, ..., \beta_{im}]^T$ is the weight of the implied layer to the output layer. $g(\cdot)$ is the implicit layer activation function, and b_i is the implicit layer bias. Then the output of the ELM network is.

$$Y = G \cdot \beta \tag{4}$$

$$\begin{aligned} &G(w_1, \ldots w_z, b_1, \ldots b_z, x_1, \ldots x_l) \\ &= \begin{pmatrix} g(w_1 \cdot x_1 + b_1) & \ldots & g(w_l \cdot x_1 + b_z) \\ \vdots & \ddots & \vdots \\ g(w_1 \cdot x_l + b_1) & \cdots & g(w_l \cdot x_l + b_z) \end{pmatrix} \end{aligned} \tag{5}$$

By determining the input weights with the hidden layer bias and loading the training set, the output weights can be determined.

$$\hat{\beta} = G^+ T \tag{6}$$

G^+ is the Moore-Penrose generalized inverse matrix of the matrix. After getting β, the training of ELM was completed. The ELM model generated from the training set is then used to make predictions for the remaining samples.

3.2. Basic principles of the artificial fish swarming algorithm

The artificial fish swarming algorithm achieves global optimisation by simulating the foraging behaviour of fish, clustering behaviour, tail-chasing behaviour and random behaviour. Assuming that there are N artificially farmed fish in a space of N dimensions and the individual state of the artificial fish is Q, it is necessary to determine the number of dimensions s of the school, the maximum number of attempts T and the crowding factor z in order to carry out the search behaviour of the school based on the above parameters [8].

(1) When food is present, the fish move as far as vision and taste allow, i.e. there exists a state Qj for which the objective function is less than the current state Qi.The full text of the article must be typeset in single column.

$$Q_i = Q_i + V \times \textbf{rand}\ () \tag{7}$$

Move to this state in a set number of steps.

$$Q_{i(t+1)} = Q_{i(t)} + \frac{Q_i - Q_{i(t)}}{\| Q_j - Q_{i(t)} \|} \times s \times \text{rand}() \tag{8}$$

If no information about the food is obtained, the existing state is kept unchanged and the search is carried out within a set field of view, repeated attempts are made, and if still no advance is made, a random act is executed[8].

(2) Crowding behaviour. The number of artificial fish is counted within the field of view, the central position Qc of the artificial fish school is found, and if the value of the objective function of the central position in the absence of crowding is less than the value of the objective function of the original state, the movement is made according to this step length.

$$\begin{cases} \|Q_i - Q_i\| < V \\ Y_c / n_i > \delta Y_i \\ Q_{i(t+1)} = Q_{i(t)} + \dfrac{Q_i - Q_{i(t)}}{\| Q_j - Q_{i(t)} \|} \times s \times \text{rand}() \end{cases} \tag{9}$$

where Yc is the objective function for the central position and Yi is the objective function for the current position. Otherwise the foraging behaviour continues.

(3) Tail-chasing behaviour. That is, if the objective function of the current position is greater than the

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objective function of the collar near the artificial fish, then the fish moves towards the neighbouring artificial fish.

$$\begin{cases} \left\| Q_i - Q_j \right\| < V \\ Y_j / n_i > \delta Y_i \\ Q_{i(t+1)} = Q_{i(b)} + \dfrac{Q_i - Q_{i(t)}}{\| Q_j - Q_{i(t)}} \times s \times \text{rand}() \end{cases} \tag{10}$$

(4) The random acts are as follows.

$$Q_{i(t+1)} = Q_{i(t)} + V \times rand() \tag{11}$$

3.3. Li-ion battery remaining life prediction model method construction

Since the input weights and thresholds are given randomly during the training and prediction process of ELM, resulting in fluctuations in the output and unreliable prediction results, a fusion of AFSA and ELM methods is proposed to optimise the selection of input weights and thresholds and optimise the ELM network using the algorithm of AFSA, where each fish passing through the path represents a candidate ELM network.

A portion of the equal voltage drop discharge time is loaded into the improved limit learning machine model for training to obtain the relevant parameters of the Li-ion battery remaining life prediction model. The first 80 sets of data are selected as the training data set, and the remaining data are the test set for prediction. The specific process is as follows.

(1) Acquisition of battery operating data: voltage drop discharge time, capacity.

(2) Loading the components into the ELM model and training the model to obtain the remaining life prediction model for lithium batteries.

(3) Loading of late equal voltage drop discharge times to obtain trends in lithium battery capacity.

(4) The mean absolute error (MAE) and root-mean-square error (RMSE) are used as assessment criteria.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i}^{n}(x_i - x_i^{'})^2} \tag{12}$$

$$MAE = \frac{1}{n}\sum_{i}^{n}| x \ - x^{'} \ | \tag{13}$$

in the formula, x_i is the true value, That is, the actual capacity of the lithium-ion battery. $x_i^{'}$ is the forecast capacity value. n is the number of cycles.

When the capacity of a Li-ion battery drops to the failure threshold, the error between the actual and predicted values of the number of cycles is defined as follows.

$$E_r = |P - R| \tag{14}$$

$$PE_r = \frac{|P - R|}{R} \times 100\% \tag{15}$$

where P is the predicted number of cycles and R is the actual number of cycles.

4. Experimental Validation and Evaluation of Results

In this section, the proposed EWT-ELM battery remaining life prediction model is validated using the NASA Prognosti-cs Center of Excellence (PCoE) B0005 and B0006 battery data sets. The battery model parameters were rated capacity 2Ah and rated voltage 4.2 V. The batteries were charged at room

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temperature in a constant current mode of 1.5A until the battery voltage reached 4.2 V, then continued to be charged in a constant voltage mode until the charging current dropped to 20 mA, and discharged at a constant current of 2A until the battery voltage dropped to 2.7 V and 2.5 V, respectively, with all three batteries being fully charged and discharged. state. The capacity was extracted from the data set and the battery capacity decline curve with the number of cycles was obtained as in Figure 2 and 3. The first 80 sets of run data were selected to train the model, and a residual health factor was loaded on the

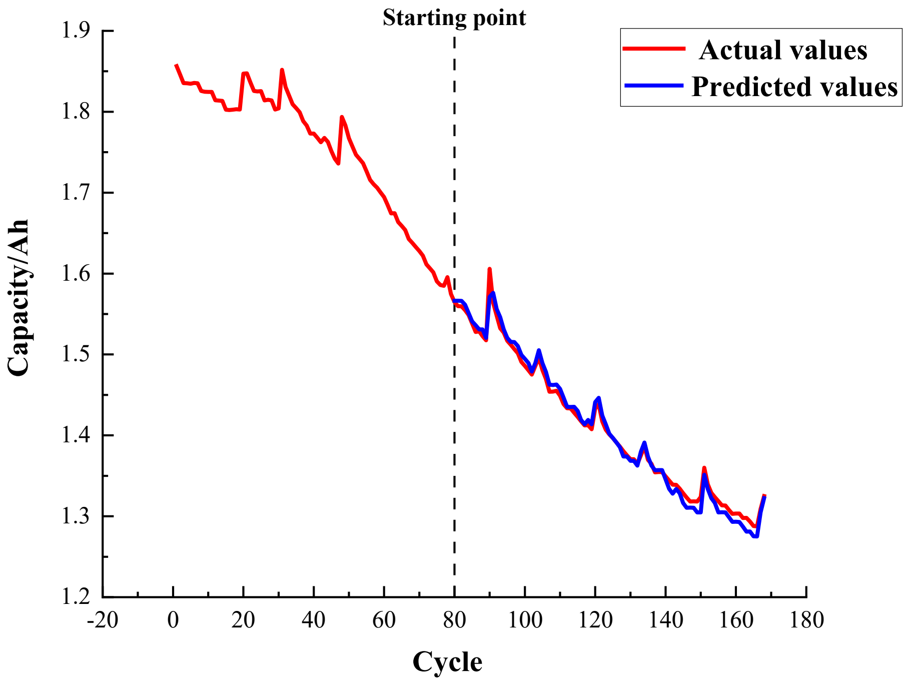

Fig 2: B0005 forecast results

well-trained model to obtain the battery capacity variation trend at a later stage.

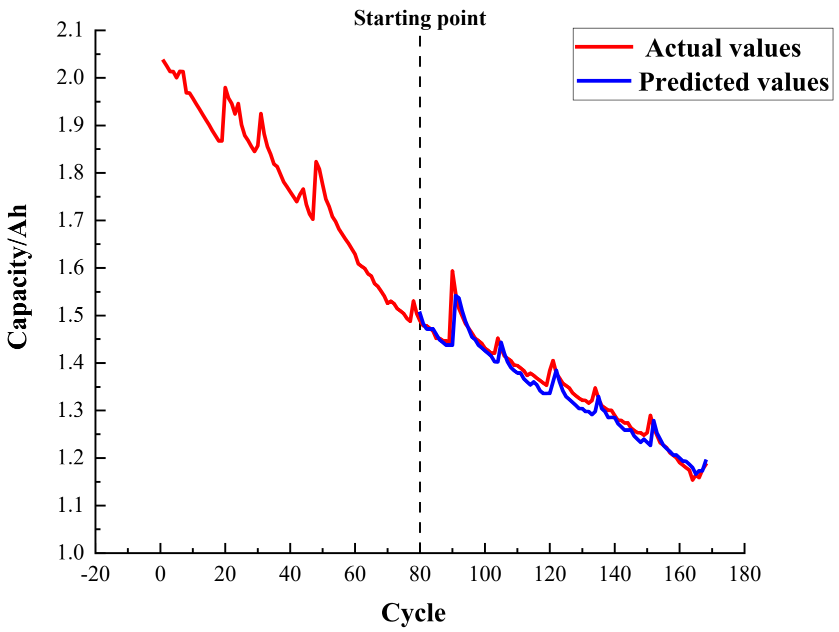

Fig3: B0006 forecast results

During the prediction process, the predictions did not jump from the results, the model was more stable and the predictions were intuitively strong in tracking capacity, indicating the validity of the proposed model. In order to analyse the experimental data more objectively, the prediction model was evaluated using RMSE, MAE, E and Per. The evaluation results are shown in Table 1.

Table 1: Results of AFSA optimization compared to GA optimization

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NO.	Method	R	P	Er	PEr	MAE	RMSE
B0005	GA-ELM[9]	101	105	5	4.95%	0.0087	0.0124
	AFSA-ELM		100	1	0.99%	0.0065	0.0115
B0006	GA-ELM[9]	99	103	4	4.04%	0.0049	0.0069
	AFSA-ELM		97	2	2.02%	0.0035	0.0055

As can be seen from the table, the ELM optimized using AFSA has higher prediction accuracy and tracks the capacity change trend better. Taken together, these results show that the proposed method constructs a valid model for predicting the remaining life of lithium batteries.

5. Conclusion

This paper proposes a method for indirect prediction of RUL of Li-ion batteries based on AFSA-ELM. By extracting the equal voltage drop discharge time as the health factor of the prediction model, introducing an artificial fish swarm optimization algorithm to optimize the model input parameters, constructing a model of the relationship between equal voltage drop discharge time and battery capacity, and setting a failure threshold to achieve indirect prediction of remaining life. Using AFSA to optimise the ELM model parameters, by comparing the prediction results of the single ELM method, the ability to describe the capacity decay trend is improved, the absolute error is reduced to 1, the problem of jumping in the prediction process of the single ELM model is solved, the model prediction accuracy and stability are improved, and the ability to track the battery capacity decline is stronger. In addition, the AFSA-ELM prediction model, compared with the genetic algorithm optimised In addition, the AFSA-ELM prediction model has lower model complexity and better real-time performance than the GA-ELM model compared to the ELM prediction model under genetic algorithm optimisation.

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