Lithium battery life prediction based on deep learning

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Abstract. Li-ion batteries have the advantages of high efficiency, high energy density and long life, having developed rapidly in recent years. However, it is tough to accurately predict the decline trend of Li-ion battery capacity, which limits the further improvement of their service life and safety. In this study, a method of using wavelet denoising to preprocess the data and predicting the life of Li-ion battery based on whale optimization algorithm combined with long short-term memory network (WOA-LSTM) is proposed. In this paper, two sets of data sets B0005 and B0006 of NASA 's public data set are used. The original battery capacity data is subjected to wavelet transform and noise reduction to remove noise and redundant information. The calculation results of SNR and RMSE are 48.1119 and 0.006225, respectively. Then LSTM (Long short-term memory), RNN (Recurrent Neural Network), GRU (Gated Recurrent Unit) and WOA-LSTM are used to predict the remaining useful life of the data set RUL (Remaining Useful Lifetime, RUL), and the data error is compared, showing that in the results of MAE, RMSE and MAPE three prediction error indicators. The prediction results of WOA-LSTM in B0005 and B0006 show the minimum prediction errors, which are 0.0563,0.0710,0.0415 in B0005 data set and 0.0583,0.0831,0.0454 in B0006 data set. Compared with the standard LSTM model, RNN model and GRU model, the error indexes of the model are decreased, which are 7 %, 4 % and 3 % respectively, which has great advantages. This method can provide a reliable predictive analysis method for battery design and fault diagnosis.

Keywords: Neural Network, Prediction Model, wavelet transform, long short-term memory, whale optimization algorithm.

1. Introduction

Li-ion batteries have high efficiency, high energy density, high cycle life and other characteristics, so they are used to a great degree in military equipment, power storage systems, aerospace and other fields [1-2]. However, during the daily charge/discharge cycle, irreversible changes occur in the electrochemical substances inside the Li-ion battery, reducing the capacity of the battery. Maintenance and replacement are required when battery capacity drops to the failure threshold (less than 70% of nominal capacity). Otherwise, it is prone to serious dangers such as battery leakage, combustion, and even explosion. Therefore, accurate evaluation and estimation of the remaining life of Li-ion batteries (RUL) can be enable to assure their long-term and reliable working[3].

There are two main means of predicting RUL: mechano-model-based methods and data-driven methods. Methods based on mechanism models cover empirical black box models, macroscopic electrochemical mechanism models, and microscopic mechanism models. However, internal and external changes during operating process of lithium batteries can affect the accuracy of the prediction of mechanical models. The data-driven system ignores the complicated mechanism inside the Li-ion battery and directly detects the battery deterioration law from the battery external condition monitoring data, thereby improving prediction accuracy and the ability to generalization of the network [4] High feasibility and practicality. Data-driven approaches are therefore widely used in RUL studies of Li-ion batteries. Data-driven models are roughly divided into models based on surface data analysis and models based on deep learning. The first widely used surface analysis-based model is an automatic regression model (AR) and its variants, which deals with time series problems by creating a linear model that treats future state values as a linear function of past state values and random error. I'll treat you. Wang et al. [5] proposed a nonlinear regression autoregressive (ND-AR) time series model for RUL prediction of lithium batteries, and processed the uncertainty using a normalized pf. Analysis methods based on surface data are highly accurate in predicting the life of Li-ion batteries.

In recent years, the divided applications of deep learning methods have been progressing. Models include support vector machines (SVM), correlation vector machines (RVM), and recursive neural networks (RNN) to accurately understand trends in Li-ion battery life. Qi et al. [6] proposed two new health indicators. These are the charge voltage difference time interval (TIEDVD) and the discharge voltage difference time interval (TIEDVD). It combines feature vector selection and support vector regression to predict RUL of lithium batteries. At first glance, RVM and SVM are the same function form, and RVM is an SVM-based method. Liu et al. [7] have proposed a method for constructing RVM prediction models by combining multiple core functions. Experimental results show that the mean absolute error and mean square error of this method are smaller than the prediction method of the optimal mononuclear correlation vector machine. The mutation long short-term memory (LSTM) algorithm and neural network (NN) model proposed by Liu et al. [8] combine multiple linear regression and recursive neural network (RNN) methods that effectively reflect regression information. This enables accurate RUL predictions.

Since the quality of data-driven prediction relies largely on the experimental data provided by the Li-ion battery life test, a large number of repeated experiments have experimental instrument accuracy errors and human factors errors, resulting in the measured experimental data often mixed with noise. The quality of RUL prediction model established by such experimental data is greatly affected. Currently, the research on Li-ion battery RUL mainly focuses on the optimization and use of various prediction models, but neglects the reasonable noise reduction of experimental data. The use of noise reduction methods in individual studies is not optimal.

In this paper, a long-short-term memory (LSTM) neural network model based on the basis of the traditional RNN, is improved to predict RUL in Li-ion batteries. Then, on this basis, a data preprocessing method using wavelet denoising is proposed to denoise the experimental data, with wavelet noise removal and the residual life prediction model of LSTM with the whale optimization algorithm (WOA).

Contribution:

(1) The Li-ion battery data is preprocessed by wavelet denoising, and the experimental distortion value is filtered out, and the redundant data unrelated to system diagnosis or irrelevant are removed, and the signal is transformed to make its characteristics decoupled or obvious. The noise reduction processing greatly reduces the experimental or human error.

(2) The LSTM model based on deep learning is used and optimized by WOA. With the support of massive data, the selective learning characteristics of memory cells greatly improve the efficiency of model data processing compared with data analysis-based methods, as well as saving time and equipment costs, and at the same time, the RUL prediction accuracy of Li-ion battery is further improved.

(3) An improved method is used to obtain a model for predicting battery RUL, providing new methods and ideas for further accurate prediction of RUL model, and it makes a certain contribution to the anchor-hold use of Li-ion batteries, as well as lays a theoretical foundation for the more accurate improvement of LSTM model in the future.

2. model introducing

2.1. Improved wavelet de-noising

Wavelet threshold noise reduction is a common digital signal processing technique that filters out noise while effectively protecting the accuracy of the effective signal. The main principle of wavelet noise reduction is the principle of wavelet transform, whose basic idea is to remove a signal from its noise using wavelets.

Assume a signal model with superimposed noise as follows:

$$s(t) = f(t) + n(t) \tag{1}$$

$f(t)$ is the original signal we want, $n(t)$ is noise. The purpose of noise reduction is to suppress $n(t)$ .If the energy of a signal is concentrated on a wavelet transform threshold few wavelet coefficients, then their values are necessarily larger than the wavelet coefficients of a large number of signals and noises after energy dispersion in the wavelet transform domain. Therefore, select the appropriate threshold value, and consider the wavelet coefficient greater than the threshold value to be generated from the signal and vice versa to be generated from the noise. The wavelet noise reduction steps are shown in figure 1:

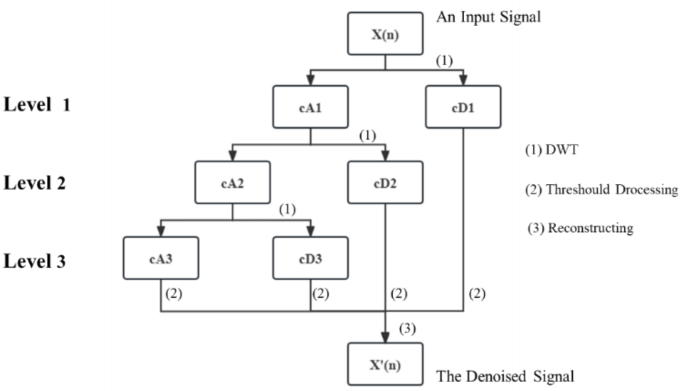


Fig 1: Wavelet noise reduction flow chart

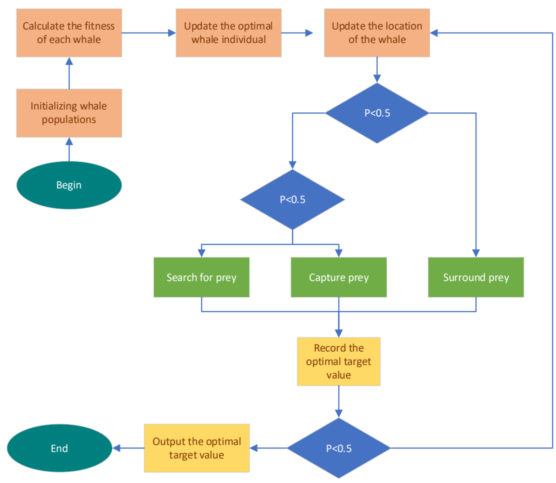


Fig 2: Whale algorithm principle

2.2. WOA-LSTM

2.2.1 whale optimization algorithm

Whale optimization algorithm is a new swarm intelligence optimization algorithm proposed by Mir Jalili and other researchers from Griffith University in Australia in 2016. It is a meta-heuristic optimization algorithm that simulates the predation behavior of humpback whales, and introduces the bubble net hunting strategy. In the WOA algorithm, the humpback whale can accurately identify the location of the prey and surround the prey. The location of each humpback whale can represent a feasible solution. The algorithm mainly includes three stages demonstrated as shown in Fig2: encircling prey, bubble-net attacking and search for prey.

2.2.2 LSTM Model

LSTM solves the problem of gradient explosion or gradient disappearance in the training process of traditional RNN, which is caused by the increase of RNN with the increase of training time and the number of network layers as shown in Fig3. In addition to adding a hidden cell state to the LSTM structure, it also adds or reduces information to the cell state by designing various ' gate ' structures, which can control the input data through the ' gate '. This data transfer method makes the weight of the self-circulation no longer fixed, and can have a long-term memory function. Therefore, LSTM has a strong advantage in dealing with the prediction and classification of time series[9].

2.2.3 WOA-LSTM Model

The key parameters of LSTM models usually depend on the empirical settings of the model builder and are highly stochastic, which usually has a dramatic impact on the ability to fit the model and may even fall into local best solutions. To address this problem, we optimize long and short-term memory neural networks using the whale algorithm. By using the number of hidden layer neurons, learning rate, and number of training iterations of the LSTM as the optimization-seeking objectives of the whale algorithm, iterative optimization is continuously performed[10].

The work of the WOA-LSTM optimization model is divided into four main parts as follows:

1) Data noise reduction processing. We use the wavelet noise reduction method for B0005 and B0006 lithium battery data to process, remove outliers and perform normalization.

2) WOA algorithm parameter setting and position initialization. Determine the maximum number of iterations (t-max), the number of whales n, the maximum value (u_b) and the minimum value (l_b) of the search range in the whale algorithm. Randomly generated population whales $X_{i,0}$(l, e, a), where l is the number of training iterations, e is the learning rate, and a is the number of hidden layer neurons.

3) WOA optimization of LSTM network parameters. The whale optimization algorithm is used to continuously iterate, select the appropriate fitness function, find the optimal individual and the optimal position, and the obtained optimal parameters are applied to the LSTM to construct the WOA-LSTM model.

4) Battery RUL prediction. The B0005 and B0006 Lithium battery test data sets were input into the WOA-LSTM model constructed using the optimal parameters, trained and the predicted values were output. the prediction block diagram of the WOA-LSTM is shown in Fig4:

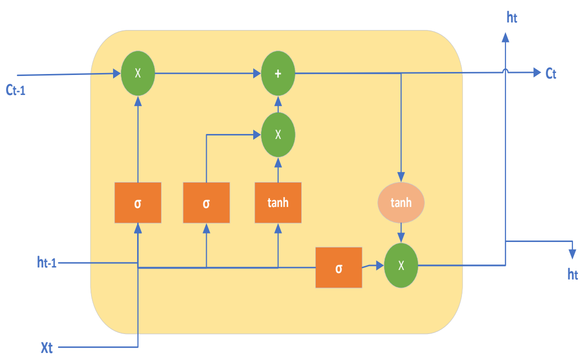


Fig 3: LSTM sketch

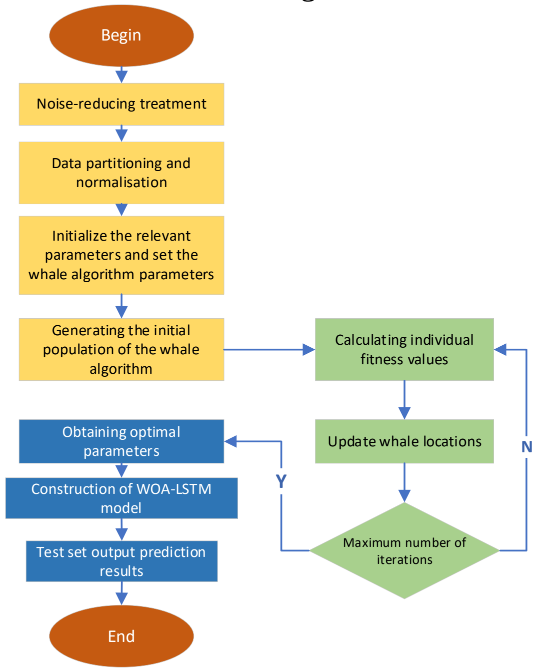


Fig 4: WOA-LSTM model prediction flow chart

3. Results

3.1. Sample selection and data sources

The paper utilizes data from NASA's public data set, which includes six experimental data points. These data points were collected by subjecting Li-ion batteries to multiple charge-discharge cycles at varying temperatures and recording their impedance after each cycle. The study focuses on four data sets, namely b0005 and b0006, which operate at room temperature and feature three different cycle modes: charging, discharging, and electrochemical impedance spectroscopy. Electrochemical impedance spectroscopy (EIS) tests were conducted to determine the parameters affecting the remaining useful life (RUL) of the battery. The electrical impedance was recorded after each charge/discharge cycle.

In charge mode, charge at 1.5A constant current (CC) mode until the battery voltage reaches 4.2V, then continue charging at constant voltage (CV) mode until the charge current drops to 20mA.

The discharge mode operates at a constant current (cc) level of 2A until the battery voltage drops to 2.7V, 2.5V, 2.2V, and 2.5V for batteries 5, 6, 7, and 18, respectively. Electrochemical impedance spectroscopy (EIS) was used to measure impedance in the range of 0.1 Hz to 5 KHz through frequency scanning. It should be noted that repeated charging and discharging cycles can accelerate battery degradation. Impedance measurement is a useful tool to gain insight into the internal parameters of a battery that may change during the degradation process. The test is considered complete when the battery reaches the end of life (EOL) standard, which is when its rated capacity drops by 30% from 2ahr to 1.4ahr.

3.2. Data noise reduction

3.2.1 Data cleaning

The evaluation indexes used in this paper are SNR and RMSE. the larger the SNR or the smaller the RMSE, the greater the proportion of effective signal components, the better the effect of noise reduction, and vice versa. the expression of SNR is as follows:

$$SNR = 10\lg\left(\frac{\sum_{i=1}^{n} f^2(i)}{\sum_{i=1}^{n}[f(i)-f(y)]^2}\right) \tag{2}$$

Where, $f(y)$ is the signal after data noise reduction, and is the signal before data noise reduction. The expression for RMSE is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[f(i)-f(y)]^2} \tag{3}$$

Where, $f(y)$ is the signal after data noise reduction, and $f(i)$ is the signal before data noise reduction.

Taking the lithium battery B0007 as an example, the total charge/discharge cycles of this battery reached 168 times. The battery capacity data of this battery is processed by noise reduction, and the calculation results of SNR and RMSE are obtained as the following table:

Table 1: Table of calculation results

	SNR	**RMSE**
Hard Threshold	42.7115	0.011592
Soft Threshold	42.7115	0.011592
Fixed Threshold	48.1119	0.006225

It can be seen from the calculation results of wavelet noise reduction that the calculation results of the fixed threshold are significantly smaller than the other two methods in terms of root mean square error, and significantly higher than the other two methods in terms of signal-to-noise ratio, so that the effective signal is better. reservation. Features: The signal analysis efficiency is higher, and the effect of extracting signal features and envelopes is also better. Therefore, we use the fixed threshold calculation method for data cleaning.

3.2.2 Noise reduction process based on WT

The number of decomposition layers is also a key consideration for wavelet noise reduction. In general, the filtering effect will be improved after increasing the number of decomposition layers, but too many decomposition layers may lead to distortion. Therefore, the number of layers we use is 3, and the noise reduction effect is shown in Figure 5.

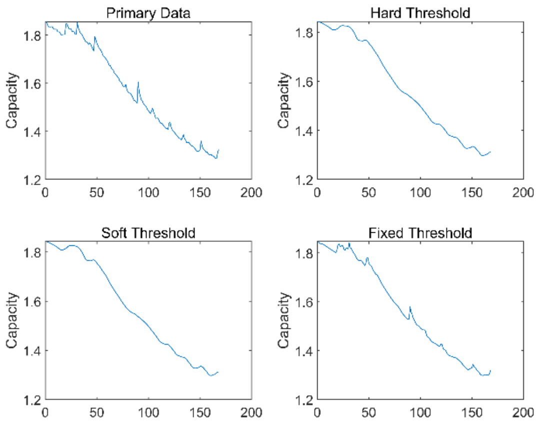


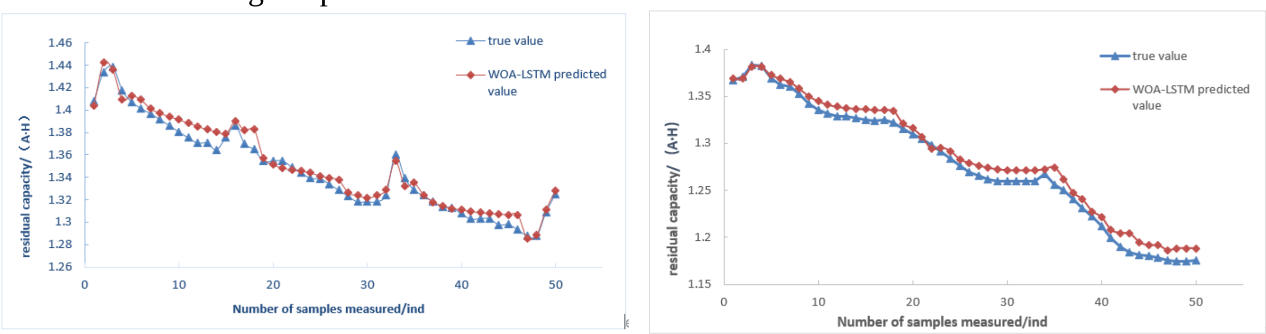
Fig 5: Noise reduction effect chart

As can be seen in Figure 5, the soft and hard thresholding noise reduction effects look similar, and the reconstructed signal shows local phenomena such as relative smoothing and the disappearance of blurred boundary details, removing the effective signal as noise. These two thresholds make the reconstructed signal lose part of the useful information of the original signal and make the correlation between the original signal and the reconstructed signal insufficient. However, the fixed thresholding effect is more consistent with the original signal and preserves a lot of important data.

3.3. Model verification

3.3.1 Analysis of effect

The whale algorithm optimization LSTM model is a recurrent neural network consisting of an input layer, a hidden layer and an output layer, with an initial number of whales of 30 and a maximum number of iterations of 100. 70% of the total lithium battery dataset is used as training data to input the neural network model, and the remaining The remaining 30% was used as the test set to validate the model. From Fig6, we can see that the real value is very close to the predicted value. This shows that the model has a good prediction effect.



(a) B0005 battery **(b) B0006 battery**

Fig 6 Predicted value and the true value of the WOA-LSTM model

3.3.2Model performance comparison

To further prove the validity of the WOA-LSTM model, three lithium battery life prediction models were selected and compared: standard LSTM model, RNN model, and GRU model.

There are many error indicators for predicting the life of lithium batteries. The paper uses three common error metrics:,mean square error (RMSE), and mean absolute error (MAE). The formula is as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right| \tag{4}$$

Here, n is the number of test set data, and y_i and $\hat{y}_i$ are the actual and predicted capacity values in time I respectively. As the RMSE and MAE values evolve, the error becomes smarter and the prediction effect improves.

The prediction error for each model is as follows:

Table 2 Prediction errors of LSTM, RNN, GRU and WOA-LSTM

evluation index	LSTM	RNN	GRU	WOA-LSTM
MAE	0.0866	0.0749	0.0905	0.0601
RMSE	0.0966	0.0848	0.0921	0.0518

The table shows the specific prediction error values for each indicator. The closer the error is to zero, the higher the prediction accuracy and the better the model. Among them, the RMSE index of Li-ion battery is the most obvious, 46.38% lower than LSTM, 38.92% lower than RNN and 43.76% lower than GRU. The MAE index is significantly lower, 30.60% lower than LSTM, 19.76% lower than RNN and 33.59% lower than GRU. Therefore, we can see that WOA-LSTM is very effective in predicting the remaining life of Li-ion batteries.

4. Conclusions

LSTM has good prediction performance, but the limitation of the above method is that the network model parameters of LSTM need to be randomly set by human experience, and the selection of different parameter training will directly affect the network model structure and prediction accuracy. In this paper, based on the above problems, we propose a method to optimize hyperparameters of the LSTM network using a whale optimization algorithm and construct a life expectancy prediction model of lithium batteries. Comparing the actual and predicted values of the three evaluation indicators leads to the following conclusion:

1) Compared with the traditional Fourier transform, wavelet de-noising can meet the non-stationary signal filtering preprocessing, it can distinguish which is the performance of the mutation part of the useful high-frequency, can solve the Fourier transform cannot give a local time period or time point on the signal frequency domain change performance.

2) The number of neurons in the hidden layer a and the initial learning rate e of the LSTM network model were optimized using WOA, and the prediction accuracy of the model was further improved by using the optimal hyperparameter combination.

3) Compared with the traditional RNN and LSTM models, the risk of falling into a local optimal solution due to artificial parameter setting is reduced, and the prediction accuracy is improved.

This method has simple structure, easy operation and high prediction accuracy. Compared with the existing battery prediction algorithms, it has better applicability and wider application value. The shortcoming of this paper is that only the data processing and prediction of B0005 and B0006 batteries are carried out. The next step is to experiment with more battery data and carry out practical application-oriented evaluation and verification.

References

[1] Tang X P, Chang F Z, Ke Y, et al. Run-to-run control for active balancing of lithium iron phosphate battery packs [J]. IEEE Transactions on Power Electronics, 2019, 35(2): 1499-1512.

[2] Lin Na, Zhu Wu, Deng 'an 'an. Prediction of residual life of Lithium ion battery based on fusion method [J]. Science Technology and Engineering, 2020, 20(5): 1928-1933. Lin Na, Zhu Wu, Deng Anquan. Remaining useful life prediction of the Li-ion battery based on fusion method [J]. Science Technology and Engineering, 2020, 20(5): 1928-1933.

[3] Pang Ying, Wang Tingting. Research progress of residual life prediction methods for lithium ion batteries [J]. Environmental Technology,202,40(06)23-27.

[4] Roozbeh R F, Shiladitya C, Mehrdad S, et al. An integrated imputation-prediction scheme for prognostics of battery data with missing observations [J]. Expert Systems with Applications, 2019, 115: 709-723.

[5] WANG D,YANG F,TSUI K L,et al. Remaining useful life prediction of Li-ion batteries based on spherical cubature particle filter ［J］. IEEE Transactions on Instrumentation and Measurement, 2016, 65(6) : 1-10 .

[6] ZHAO Qi, QIN Xiaoli, ZHAO Hongbo, et al . A novel prediction method based on the support vector regression for the remaining useful life of Li-ion batteries[J].Microelectronics Reliability, 2018, 85: 99-108 .

[7] LIU Yuefeng, ZHAO Guangquan, PENG Xiyuan . A Li-ion battery remaining using life prediction method based on multi-kernel relevance vector machine optimized model [J].Acta Electronica Sinica, 2019,47(6) : 1285-1292 . (In Chinese)

[8] Shunli Wang, et al, A critical review of improved deep learning methods for the remaining useful life prediction of Li-ion batteries, [J]. Energy Reports,2021, Volume 7:5562-5574.

[9] Wang S , Jin S , Bai D , et al. A critical review of improved deep learning methods for the remaining useful life prediction of Li-ion batteries[J]. Energy Reports, 2021, 7:5562-5574.

[10] Hao Keqing, Lu Zhigang, Di Ruohai et al. Optimized long and short term memory neural network based on whale algorithm for remaining life prediction of lithium batteries[J]. Science, Technology and Engineering, 2022,22(29):12900-12908.