Abstract
Lithium battery is a new energy equipment. Because of its long service life and high energy density, it is widely used in various industries. However, as the number of uses increases, the life of the energy battery gradually decreases. Aging of battery will bring security risks to energy storage system. Through the life prediction of energy lithium battery, the health status of energy battery is assessed, so as to improve the safety of energy storage system. Therefore, a hybrid model is proposed to predict the life of the energy lithium battery. The lithium-ion battery capacity data are always divided into two scales, which are predicted by extreme learning machine and support vector machine model. The energy lithium-ion battery capacity attenuation data were obtained through experiments. The original signal is decomposed into five layers by using the wavelet basis function to denoise the signal. Finally, the denoised signal is synthesized. The noise reduction effect of each wavelet was analyzed. The analysis results show that the mean square error value of the Haar wavelet is 5.31e-28, which indicates that the Haar wavelet has the best noise reduction effect. Finally, the combined model was tested by using two sets of experiments. The prediction results of the combined model are compared with those of the single model. The test results show that the prediction results of the combined model are better than the single model for either experiment 1 or experiment 2. Experiment 1 indicated the root
mean square error values are 29.58 and 79.68% smaller than the root mean square error values of extreme learning machine and support vector machine. The model proposed in this study has positive significance for the safety improvement of energy storage system and can promote the development and utilization of energy resources.

**Keywords**

Energy lithium-ion battery, life prediction, energy storage system, artificial intelligence algorithm, hybrid model

**Introduction**

As environmental pollution becomes more and more dangerous, countries around the world are keen to develop and utilize new energy sources. The development of clean energy (such as solar, wind, etc.) has an important impact on improving environmental quality (Baleta et al., 2019; Karchiyappan, 2019; Tseng et al., 2018; Wang, 2016; Wang et al., 2019a, 2018). Energy lithium battery is widely used in energy storage system because of its high energy density, long service life, and environmental protection. However, with the increase of service time, the service life of energy lithium battery will be reduced and the battery will appear aging problems. If the aging battery cannot be replaced in time, it will affect the safe and stable operation of the energy storage system. So the health status of energy lithium battery is an important indicator of energy storage system and the health status is evaluated by predicting the remaining life of the lithium battery to provide reliable data support for the energy system (Ungurean et al., 2017). Improving the health assessment level of lithium batteries is of considerable significance to the electric vehicle industry.

In the literatures, Mishra et al. (2018) proposed the Bayesian hierarchical model to assess the reliability of lithium batteries and the model predicts the termination life of batteries under different loads. This method is used not only for health assessment of a single cell but also for health assessment of the whole battery pack. The lithium inventory directly affects the aging degree of lithium batteries. Coulomb efficiency has a strong relationship with lithium inventory. The aging degree of lithium batteries is evaluated by coulomb efficiency. Yang et al. (2019) proposed a coulombic efficiency-based model. In this method, the parameters of the model are updated by a particle filter, and the online battery health status is evaluated. The coulombic efficiency-based model has better fitting performance compared with the square root time model. Cai et al. (2019) proposed a novel method to estimate the state of health of lithium batteries. This method is based on an evolutionary framework. The most practical combination of short-term and medium-term characteristics in pulse testing is selected by the evolutionary framework. The support vector regression is used to estimate the state of health of lithium batteries. This method is based on an evolutionary framework. The most practical combination of short-term and medium-term characteristics in pulse testing is selected by the evolutionary framework. The support vector regression is used to estimate the state of health of lithium batteries. Liu et al. (2018) proposed a self-adaptive life cycle health state assessment method. This method is based on the least squares support vector machine (LSSVM). The health status of lithium batteries is evaluated by mapping the feature space to the capacity space. Prior studies mostly use a single model to assess the health status of lithium batteries. Limitations of a single model can affect evaluation results. For example, Bayesian method is very sensitive to the expression of input data, and the particle filter depends heavily on the estimation of initial state. Aiming at the problems
of the methods proposed by experts in the above literature, this study proposes a hybrid model. The simulation results show that the hybrid model has higher prediction accuracy and stability.

Hence, the objectives of this study are as follows: (1) different wavelet basis functions are used to denoise the original signal, and the denoising effects of different wavelet basis functions are compared; (2) the SVM model and extreme learning machine (ELM) model are used to predict the remaining life of energy lithium batteries, and the prediction trends of the two models are compared; (3) the ELM-support vector machine model is established to predict the remaining life of lithium batteries, and the BSA algorithm is used to optimize the parameters of SVM; (4) different evaluation indicators are used to evaluate the method proposed in this study. The contributions of this study are with four-fold. (1) The original data are pre-processed before the life prediction of lithium batteries. (2) This study introduces the ELM–BSASVM combination method to assess the health status of the cell. The prediction effect of the proposed combination method is better. (3) By predicting the cell life, the health status of the cell is evaluated to provide reliable data support for the energy storage system. (4) Improving the health assessment level of lithium batteries is of considerable significance to the energy storage system.

The main contents of sections 1 to 6 are organized as follows. In Section 1, the literature on the methods of predicting the residual life of lithium batteries is introduced. Section 2 mainly presents the aging test of lithium batteries. Section 3 introduces the wavelet denoising test. Section 4 introduces the basic principles of support vector machines and ELM. Section 4 presents the lithium-ion battery life prediction simulation test. Section 6 introduces the implications. Section 6 mainly introduces the essential conclusions of this study.

Literature review

Forecasting the remaining life of the lithium-ion battery

When the capacity of the battery decays to 70% to 80% of the rated capacity, the battery is considered to be invalid (Li et al., 2017a, 2019a, 2017b; Wu and Moo, 2017). Currently, forecasting methods include modeling methods and intelligent algorithms based on data (Li et al., 2019b; Wang et al., 2019b; Zhou et al., 2019). The modeling method is mainly to model the lithium-ion battery mathematically. The disadvantage is that modeling is difficult. The more common methods are based on data-driven prediction, such as particle filter, support vector machine, relevant vector machine, Kalman filter, and others (Chen et al., 2019; Lin et al., 2016; Peng et al., 2018; Tao et al., 2018; Wang et al., 2018). The data-driven prediction method uses the prediction model to explore the data. The model indicates the relationship between the relevant variables and the lithium-ion battery capacity attenuation. This method is relatively simple, but the setting of the model parameters has a more significant impact on the prediction results.

Ahwiadi and Wang (2019) improved particle filter and applied the improved particle filter algorithm to battery life prediction. In the improved particle filter, the low-quality particles are solved. The outlier evaluation strategy is introduced to the new method, which can examine the posterior distribution pattern. Li et al. (2019a) used the LSSVM for forecasting the residual life. The parameters of LSSVM are optimized by improved bird swarm optimization algorithm. However, the original data were not pre-processed before the life
forecasting. The noise signal in raw data will affect the prediction effect of the model. Zhang et al. (2019b) combined relevance vector machine and particle filter to predict the remaining useful life of the Li-ion battery. The hybrid method can effectively reduce the number of training samples compared with the traditional prediction method, which can reduce the time of fault prediction.

Cadini et al. (2019) proposed a method to forecast the battery life. This method combines particle filter and neural network to construct parameter observation equation. And this method can automatically adapt to the dynamic behavior of different batteries. Downey et al. (2019) proposed a physics-based method to predict the life of Li-ion batteries. In this method, the residual life of lithium-ion batteries is predicted on-line by tracking the degradation parameters with the nonlinear least squares method of a dynamic boundary. The uncertainty in the process of life prediction of lithium-ion batteries is reduced through the dynamic boundary. A life prediction model for lithium-ion batteries combined the capacity degradation trajectory and internal resistance growth model of lithium-ion batteries (Guha and Patra, 2018). The combined model is more stable in prediction compared with the single prediction model.

In sum, prior studies are absent on data preprocessing. Hence, in this study, the wavelet transform is used to denoise the capacity degradation data of lithium-ion batteries, and the ELM–BSASVM model is presented to predict the residual life of lithium-ion batteries.

The proposed method
Zhang et al. (2019a) introduced the Box–Cox transformation into the field of life forecasting. The capacity data is converted by the Box-Cox transformation. The linear predictor is constructed between the conversion data and the number of cycles. A combined energy storage system composed of cells and super capacitors can increase the service life of the lithium-ion battery. Liu et al. (2019) improved the degradation model of cells. The current factor is taken into account in the degradation model. And the short-term forecasting model and long-term forecasting model are used to forecast the health indicators.

Li et al. (2016) used a Gaussian mixture method to forecast cell life. In this method, different trajectory segments are predicted by using different Gaussian regression models. The advantage of the Gaussian mixture model is that it can generate prediction confidence intervals compared to other traditional prediction models. Wang and Mamo (2018) introduced support vector machine, and the support vector machine parameters are optimized by differential evolution algorithm. Yang et al. (2018) introduced the ELM to forecast cell life. The parameters of the ELM are optimized by heuristic Kalman algorithm.

The method proposed in this study is given as follows. (1) The original signal is decomposed into five layers by using the Haar wavelet, db4 wavelet, sym4 wavelet, and coif.4 wavelet. The two evaluation indexes of MSE and signal-to-noise ratio (SNR) are used to evaluate the noise reduction effects of the four wavelets, and finally, the optimal noise reduction data are selected. (2) The SVM model and the ELM model are used to assess the health status of cells. The prediction effects of the two models are analyzed. (3) The combination model, BSA algorithm is used to optimize the parameters of SVM to improve the prediction effect. The remaining life is forecasted by the ELM–BSASVM combination method. (4) The root mean square error (RMSE), absolute error (AE) and $R^2$ are used as detection indexes of the forecasting model.
Battery capacity attenuation experiment

The lithium-ion battery charging and discharging experimental equipment includes a temperature box, a high-precision battery performance test system, and a computer. The battery terminal voltage of the cell and the current flowing through the cell are recorded by the performance test system. Moreover, the battery performance test system also directly generates the curves of voltage, current, and other recorded values. The experiment operation flow chart is as Figure 1.

The capacity of the lithium-ion battery used in the test is 2/A h; the temperature of the temperature chamber is set to 25°C. The charging and discharging operations of the cell are executed in the temperature chamber. The battery aging experiment mainly includes the following two stages.

1. The charging experiment of lithium batteries is carried out. The charging rate is set to 1.0°C, the charging cut-off current is set to 20 mA, and the charging cut-off voltage is set to 4.2 V. When the charging experiment of lithium batteries is completed, the sustainable lithium batteries are placed for half an hour.
2. Then, the discharging experiment of lithium batteries is carried out. The discharging rate is set to 1.0°C, and the cut-off voltage is set to 2.5 V. When the discharging experiment of cells is completed, the cells are placed for half an hour. The charging experiment and discharging experiment of lithium-ion cells are repeated.

The degradation curve of lithium-ion cell capacity obtained from the cell aging test is as follows.

When the capacity of cells deteriorates to 80% of the rated capacity, the sustainable lithium batteries are considered to be invalid and the experiments on sustainable lithium batteries are repeated.

![Figure 1](image-url). The lithium-ion battery experimental operation flow chart.
batteries are stopped. Figure 2 presents the failure threshold of the lithium-ion cell used in
the experiment as 1.8/A h.

Preprocessing of experimental data

Obtaining the capacity data degradation curve is an essential and fundamental step in the life forecasting of batteries. The capacity degradation data of the cell have an impact on the prediction effect. In the process of capacity decay of lithium batteries, there are many factors that affect the capacity of lithium batteries, such as experimental temperature, discharge rate, and charge–discharge voltage. These factors cause the lithium battery capacity attenuation data to be doped with a particular noise signal. If the model is trained and predicted directly by using raw data, the noise signal affects the model’s forecasting accuracy. Therefore, the raw capacity data of the cell are pre-processed to filter out the noise signal in the original signal.

Traditional filtering methods mainly include a nonlinear filter and linear filter, such as mean filter, Wiener filter, and so on. The traditional noise reduction methods are dependent on the Fourier transform, which can only change all signals into time domain or frequency domain. It cannot describe the non-stationary characteristics of signals and cannot get the correlation of signals. The wavelet transform has good time domain characteristics and frequency domain characteristics. Also, the wavelet transform has the advantages of low entropy, multi-resolution, wavelet base selection diversity, and decorrelation. In general, a one-dimensional noisy signal can be expressed as follows (Xu et al., 2016; Zhang et al., 2019)

\[ g_i = f_i + \lambda e_i \]  

(1)

where \( g_i \) is the noisy original signal, \( f_i \) is the real signal, \( e_i \) is the noise signal, and \( \lambda \) is the noise level. The process of wavelet denoising is as follows:

1. The original signal is resolved into a high-frequency part and a low-frequency part by wavelet transform. Generally, the low-frequency signal is a real signal and the high-frequency signal is a noise signal.

![Figure 2. The capacity degradation curve of lithium-battery.](image)
2. The high-frequency signals are processed.
3. The wavelet is reconstructed and the denoised signal is output.

The process of wavelet denoising is shown in Figure 3.

The conventional wavelet basis functions are shown in Table 1.

The conventional Haar wavelet, coif.4, db4 wavelet, and sym4 wavelet are used to decompose the original signal into three layers. And the fixed threshold is used, and the threshold function adopts the soft threshold function. The data after the noise reduction of the lithium-ion battery data are shown in Figure 4.

The absolute difference curve between the denoising signal and the original signal is shown in Figure 5.

The variance and SNR are used as evaluation indicators to evaluate the denoising effects of Haar wavelet, coif.4, db4 wavelet, and sym4 wavelet

\[
MSE = \frac{1}{m} \sum_{j=1}^{m} (k_j - k_j^*)^2
\]

where \(k_j\) is the raw data (noisy signal) and \(k_j^*\) is the data after denoising.

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**Table 1.** The characteristics of basis function.

| Basis function | Characteristics |
|----------------|-----------------|
| Haar           | Discontinuous in time domain but simple calculation |
| dbN            | The time domain is finitely supported and the wavelet length is limited |
| coif. N        | Good symmetry |
| Gaussin        | Non-orthogonal wavelet, scaleless function |
| Mexh           | Wavelet functions are not orthogonal |
| BiorNr. Nd     | Linear phase characteristics |
| Meryer         | Fast convergence |
| Morlet         | No scaling function |
| Sym. N         | Good symmetry and reduced phase distortion |
Figure 4. Denoising results of four wavelets: (a) the denoising result of Haar wavelet, (b) the denoising result of db4 wavelet, (c) the denoising result of sym4 wavelet, and (d) the denoising result of coif.4 wavelet.

Figure 5. Absolute difference curve between the denoising signal and the original signal.
The variance mainly reflects the disparity between the raw data and the data after denoising. The smaller the variance and the better the denoising effect

\[ SNR = 10 \times \log \left( \frac{\sum_{j=1}^{m} k_j^2}{\sum_{j=1}^{m} (k_j - k_j^*)^2} \right) \]  

(3)

The ratio of the raw data to the noisy data is the SNR. The greater the SNR and the more obvious the denoising effect. The denoising effects of four wavelet functions are shown in Table 2 and Figure 6.

By analyzing the data in Table 2, the data gap between the MSE and the SNR of coif.4, db4 wavelet, and sym4 wavelet is not very large, and the denoising effects of the three wavelets are similar. The MSE value of Haar wavelet is the smallest, and its SNR value is close to the SNR values of the other three wavelets compared with the other three wavelet functions. After a comprehensive comparison, the data after Haar wavelet processing is selected as the experimental simulation data.

Lithium-ion battery health assessment model

**SVM regression principle**

SVM is suitable for small sample prediction and classification problems and has strong nonlinear mapping ability. By introducing a mapping kernel function in SVM, a nonlinear

| Wavelet function | MSE        | SNR   |
|------------------|------------|-------|
| Haar             | 5.31e-28   | 57.56 |
| db4              | 2.64e-08   | 63.80 |
| sym4             | 4.80e-10   | 60.51 |
| coif.4           | 8.17e-09   | 64.96 |

MSE: mean square error; SNR: signal-to-noise ratio.

Figure 6. Evaluation of noise reduction effect: comparison of MSE values of four kinds of wavelet denoising (left); comparison of SNR values of four kinds of wavelet denoising (right). MSE: mean square error; SNR: signal-to-noise ratio.
regression is transformed into a d-dimensional linear regression through mapping, which avoids dimensionality disaster and improves the regression efficiency of the algorithm (Du et al., 2018; Wang et al., 2018; Zhang et al., 2018). SVM is widely used in image processing, pattern recognition, fault diagnosis, and other fields.

Assume that the sample set \( \{(u_1, v_1) \cdots (u_m, v_m)\} \in \mathbb{R}^d \times \mathbb{R} \) is known. The SVM maps the data set to the d-dimensional space by mapping the kernel function. In high dimensional space, the regression function is constructed. The specific implementation method of the SVM is as follows (Gola et al., 2019; Jiang et al., 2018; Li et al., 2018)

\[
f(u) = e\varphi(u) + \gamma
\]

where \( e \) is the weight, \( f(u) \) is the prediction function, \( \varphi(u) \) is the data set mapping function, and \( \gamma \) is the threshold vector.

The insensitive loss function \( d \) is introduced, and equation (4) is converted according to the principle of risk minimization (Melgani and Bruzzone, 2004; Smola and Scholkopf, 2004)

\[
\min \frac{1}{2} \|e\|^2 \\
\text{s.t.} \begin{cases}
    v - e\varphi(u) - \gamma \leq d \\
    e\varphi(u) + \gamma - v \leq d
\end{cases}
\]

(5)

The slack variable \( \theta \) is introduced in equation (5). The target minimization problem is as follows

\[
\min \frac{1}{2} \|e\|^2 + o \sum_{i=1}^{m} (\theta_i + \theta_i^*) \\
\text{s.t.} \begin{cases}
    v - e\varphi(u) - \gamma \leq d + \theta_i \\
    e\varphi(u) + \gamma - v \leq d + \theta_i^* \\
    \theta_i, \theta_i^* \geq 0
\end{cases}
\]

(6)

where \( o \) is the punishment quantity, and the size of the penalty will change with the degree of the crossing.

The Lagrangian function is used to convert the minimization problem into a dual problem

\[
L = \frac{1}{2} \|e\|^2 + o \sum_{i=1}^{m} (\theta_i + \theta_i^*) - \sum_{i=1}^{m} \mu_i (d + \theta_i - v_i + e\varphi(u_i) + \gamma) \\
- \sum_{i=1}^{m} \mu_i^* (d - \theta_i^* + v_i - e\varphi(u_i) - \gamma) - \sum_{i=1}^{m} (l_i \theta_i - l_i^* \theta_i^*)
\]

(7)

where \( \mu \) is a Lagrangian multiplier.

The weight \( e \) obtained by solving equation (7) is brought into equation (4) to obtain the regression function

\[
f(u) = \sum_{i=1}^{m} (\mu_i - \mu_i^*) (\varphi(u_i) \cdot \varphi(u)) + \gamma
\]

(8)
The principle of ELM

ELM is a new framework for feedforward neural networks (SLFN). ELM overcomes the shortcomings of SLFN which is slow in solving and has poor global search ability (Liang et al., 2019; Raghuwanshi and Shukla, 2019). The connection weights and thresholds of ELM are established randomly and remain unchanged in the process of iteration. In ELM, the number of neurons in the hidden layer needs to be set. ELM has the characteristics of fast speed and generalization ability. ELM is widely used in classification, forecasting, and other fields.

The structure of ELM is divided into three layers, each layer is composed of neurons, and each layer is connected by weights. Assume that the number of input, hidden, and output neurons is p, e, and t (Huang et al., 2015; Liu et al., 2020).

Between the hidden segment and the input segment, the weight vector is \( a \). Among the output segment and the hidden segment, the weight vector is \( b \). The threshold value of the hidden segment neurons is \( c \) (Ali and Prasad, 2019; Miche et al., 2010)

\[
a = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1p} \\ a_{21} & a_{22} & \cdots & a_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ a_{e1} & a_{e2} & \cdots & a_{ep} \end{bmatrix}_{e \times p}, \\
b = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1t} \\ b_{21} & b_{22} & \cdots & b_{2t} \\ \vdots & \vdots & \ddots & \vdots \\ b_{e1} & b_{e2} & \cdots & b_{et} \end{bmatrix}_{e \times t}, \\
c = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_e \end{bmatrix}_{e \times 1}
\]  

(9)

A sample set \( M \) is provided. The input matrix and output matrix of the sample are \( S \) and \( F \)

\[
S = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1M} \\ s_{21} & s_{22} & \cdots & s_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ s_{p1} & s_{p2} & \cdots & s_{pM} \end{bmatrix}_{p \times M}, \\
F = \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1M} \\ f_{21} & f_{22} & \cdots & f_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ f_{t1} & f_{t2} & \cdots & f_{tM} \end{bmatrix}_{t \times M}
\]  

(10)

The hidden layer activation function is \( \psi \) and the ELM output is \( G = [g_1, \ldots, g_M]_{t \times M} \)

\[
g_i = \begin{bmatrix} g_{i1} \\ \vdots \\ g_{it} \end{bmatrix}_{t \times 1} = \begin{bmatrix} \sum_{j=1}^{e} b_{i1} \psi(a_{ij} s_j + c_i) \\ \vdots \\ \sum_{j=1}^{e} b_{it} \psi(a_{ij} s_j + c_i) \end{bmatrix}_{t \times 1} 
\]  

(11)

where \( a = [a_{i1}, \ldots, a_{it}] \), \( s = [s_{1j}, \ldots, s_{pj}] \).
Equation (11) is expressed as equation (12)

\[
Rb = G^T \\
R = \begin{bmatrix}
\psi(a_1 \cdot b_1 + c_1) & \cdots & \psi(a_e \cdot b_1 + c_e) \\
\vdots & \ddots & \vdots \\
\psi(a_1 \cdot b_M + c_1) & \cdots & \psi(a_e \cdot b_M + c_e) \\
\end{bmatrix}_{M \times e}
\]

The connection weight \( b \) of the ELM is obtained by the least squares solution

\[
\hat{b} = R^+ G^T
\]

where \( R^+ \) is the generalized inverse matrix of \( R \).

**Lithium-ion battery health status assessment**

Lithium-ion cell life prediction is a vital part of assessing health status. By forecasting the life of lithium-ion cells, the data of failed batteries are obtained, which provide reliable data support for battery health status assessment. The primary process of battery health status assessment is shown in Figure 7.

Figure 7 presents the health assessment of lithium batteries and is divided into the following several steps.

1. The failure threshold of lithium battery, test samples, and training samples of the forecasting model are selected.
2. The life prediction model is trained with training samples.
3. The life forecasting model is tested with testing samples. And the evaluation index is used to assess the test results of the model.
4. The health status of lithium batteries is assessed.

![Figure 7. Lithium-ion battery health status assessment.](image-url)
Simulation experiment and result discussion

The SVM model, the ELM model, and ELM–BSASVM model are tested by two sets of data. The number of samples of the three prediction models is shown in Table 3.

The RMSE, AE, and determinant coefficient $R^2(0 \leq R^2 \leq 1)$ are taken as the evaluation indexes of the prediction model. The smaller the RMSE is, the smaller the error is, the stronger the forecasting stability of the model is. When the determinant coefficient $R^2$ is closer to 1, the better the fitting result of the forecasting model is. When the determinant coefficient $R^2$ is closer to 0, the difference between the estimated value of the model and the actual value is larger. The expressions of AE, RMSE, and $R^2$ are as shown in equations (14) to (16)

$AE = \hat{k} - k$  \hspace{1cm} (14)

$RMSE = \sqrt{\frac{1}{l} \sum_{i=1}^{l} (\hat{k}_i - k_i)^2}$  \hspace{1cm} (15)

$R^2 = \frac{\left( \sum_{i=1}^{l} \sum k \hat{k} - \sum k \sum \hat{k} \right)^2}{\left( \sum (\hat{k})^2 - \sum (k)^2 \right) \left( \sum (k)^2 - \sum (k)^2 \right)}$  \hspace{1cm} (16)

where $\hat{k}$ is the output of the prediction model and $k$ is the actual value.

Health assessment of lithium battery based on SVM and ELM models

First, the life of a lithium-ion battery is predicted by the SVM model. The data in Table 3 are used to test SVM. The test results of experiment 1 and experiment 2 are shown in Figure 8.

Figure 8 indicates that the forecasting stability of the SVM model is very high, and the forecasting curve trend of SVM is similar to the attenuation trend of the real value curve. The SVM model has strong robustness. Moreover, the prediction stability is still maintained in the later stage of the prediction.

From the relative error curve, the test samples are 258 and 158, the fluctuation of the prediction curve is not obvious, and the maximum relative error is maintained at about 1%.

Second, the ELM model is used to forecast the life of the cell. The ELM is tested by testing data in Table 3. The simulation results of experiment 1 and experiment 2 are shown as follows.

Figure 9 shows that the prediction trend of ELM changes obviously with the increase of the number of test samples in both experiment 1 and experiment 2. Especially in the later stage of the prediction.

Table 3. The sample number of prediction models.

| Experiment   | Training samples | Testing samples | Remaining life value |
|--------------|------------------|-----------------|---------------------|
| Experiment 1 | 800              | 258             | 193                 |
| Experiment 2 | 900              | 158             | 93                  |
Figure 8. Prediction results of SVM model. (a) Test results of the SVM model in experiment 1, (b) test errors of the SVM model in experiment 1, (c) test results of the SVM model in experiment 2, and (d) test errors of the SVM model in experiment 2. SVM: support vector machine.

Figure 9. Prediction results of ELM model. (a) Test results of the ELM model in experiment 1, (b) test errors of the ELM model in experiment 1, (c) test results of the ELM model in experiment 2, and (d) test errors of the ELM model in experiment 2. ELM: extreme learning machine.
stage, the prediction error of the ELM model increases obviously, indicating that the forecasting stability of ELM is poor. The robustness of the ELM model is weak. For experiment 1, the relative error of the ELM model in the later stage of prediction exceeds 20%, and the prediction effect is weak. For experiment 2, the relative error of the ELM model exceeds 3% in the later stage of prediction. The result of experiment 2 is better than that of experiment 1, which shows that the number of samples has a significant influence on the forecasting effect of ELM. With the increase of training samples, the prediction error of the ELM model decreases relatively.

Figure 9 shows that the ELM has a better prediction effect in the early stage of prediction. For experiment 1, the ELM model has a better prediction effect for the first 100 test samples than the last 158 test samples. And the prediction errors of the first 100 test samples are all controlled within 1%. For experiment 2, ELM has higher prediction stability for the first 60 samples, and the prediction errors are also controlled within 1%.

In the early stage of prediction, the RMSE and \(R^2\) values of the two models are compared as shown in Figure 10.

Comparing with experiment 1 and experiment 2 data in Figure 10, the \(R^2\) values of SVM and ELM models are similar in the early stage of prediction. The \(R^2\) values of both models are about 0.9, which indicates that the fitting effect of the two models is similar. But the RMSE values of SVM and ELM models are quite different. For experiment 1 and experiment 2, the RMSE of the SVM model is about 0.5%.

Experiment 1 showed the RMSE of the ELM model is about 0.3%. Experiment 2 presented the RMSE of the ELM model is about 0.3%. ELM’s RMSE value is about 0.2%. The ELM’s RMSE value is significantly smaller than SVM’s RMSE in both experiment 1 and experiment 2. From the comparison of the data in Figure 10, the forecasting effect of ELM is better than SVM in the early stage of prediction.

Health assessment of lithium battery based on ELM–BSASVM combination model

In SVM, the penalty coefficient and gamma parameter have a significant influence on the regression effect of the model. In this study, bird swarm optimization algorithm is used to optimize the parameters of SVM.

![Figure 10](image)

**Figure 10.** Analysis of RMSE and \(R^2\) in the early stage of prediction models. (a) Analysis of RMSE and (b) analysis of \(R^2\). ELM: extreme learning machine; RMSE: root mean square error; SVM: support vector machine.
Bird swarm optimization is a new bionic intelligent algorithm, which simulates the foraging and migration behavior of birds. The BSA algorithm has the following rules (Meng et al., 2016; Wu et al., 2018):

1. Each bird in the flock has both feeding and alert behavior and maintains one of these behaviors.
2. The foraging experience in the flock is shared. Individuals can forage based on group experience.
3. Each bird strives to fly to the center of the group.
4. Birds regularly migrate to other locations for food.
5. After updating the position of the flock, the birds are divided into followers and producers based on food reserves. The bird with the highest food reserve becomes the producer, the bird with the lowest food reserve becomes the follower, and the other birds randomly choose two roles.
6. Producers lead their followers to search for food.

For rule (1), each bird chooses foraging behavior and alert behavior according to random number $L$.

For rule (2), $Position_{ij}(t) \in [1, 2, \ldots, D]$ denotes the position of the $i$th bird in the $j$-dimensional space at time $t$.

When a bird is foraging, its position is as follows

$$Position_{ij}(t + 1) = Position_{ij}(t) + E \cdot rand(0, 1) \cdot (P_{i}^{best} - Position_{ij}(t)) + \ldots + R \cdot rand(0, 1) \cdot (g_{best} - Position_{ij}(t))$$

(17)

where $rand$ indicates a random number, $P_{i}^{best}$ indicates the best position of the individual, $g_{best}$ represents the global best position, $E (E > 0)$ indicates the learning coefficient, and $R (R > 0)$ represents the social cognitive coefficient.

When the bird chooses alert behavior, its position is as follows

$$\begin{cases} Position_{ij}(t + 1) = Position_{ij}(t) + rand(0, 1) \cdot Q_{1}(Position_{j}^{mean} - Position_{ij}(t)) + \ldots + rand(-1, 1) \cdot Q_{2}(Position_{kj} - Position_{ij}(t)) \\ Q_{1} = q_{1} \cdot e^{\frac{Fitness_{ij} \cdot M}{Fitness_{sum} \times \bar{e}}} \\ Q_{2} = q_{2} \cdot e^{\frac{Fitness_{ij} - Fitness_{kj}}{Fitness_{sum}} + \epsilon \frac{Fitness_{ki} - Fitness_{kj}}{Fitness_{sum} + \epsilon}} (k \neq i, k \in [1, n]) \end{cases}$$

(18)

where $Position_{j}^{mean}$ denotes the average value of the position in the $j$th dimension, $q_{1}, q_{2} \in [0, 2]$, $\bar{e}$ is an infinite decimal, and $Fitness_{sum}$ represents the sum of fitness values.

The producer location is as follows

$$Position_{ij}(t + 1) = Position_{ij}(t) + Position_{ij}(t) \cdot randn(0, 1)$$

(19)

The follower location is as follows

$$Position_{ij}(t + 1) = Position_{ij}(t) + (Position_{kj}(t) - Position_{ij}(t)) \cdot F \cdot rand(0, 1)$$

(20)

where $F \in [0, 2]$ is the following coefficient.
BSA algorithm
Start
Initialize population $pop$, maximum number of iterations $M$, $q_1$ and $q_2$;
Initialize individual fitness values $Fitness$ and find out $P_{i}^{\text{best}}$ and $g_{\text{best}}$;
While ($t < M$)
    if ($t = \text{FQ} \ (\text{Migration frequency})$)
        Calculate $Position_{j}^{\text{mean}}$ and $Fitness_{\text{sum}}$;
        if ($\text{rand} > L$)
            Update individual position $Position_{ij}(t + 1)$ according to equation (17) and calculate fitness value $Fitness$;
        else if ($\text{rand} < L$)
            Update individual position $Position_{ij}(t + 1)$ according to equation (18) and calculate fitness value $Fitness$;
        end if
    else if ($\text{rand} > L$)
        Update the producer position $Position_{ij}(t + 1)$ according to equation (19) and calculate the fitness value $Fitness$;
    else
        Update the follower position $Position_{ij}(t + 1)$ according to equation (20) and calculate the fitness value $Fitness$;
    end if
    Update individual optimal position $P_{i}^{\text{best}}$ and global optimal position $g_{\text{best}}$;
    Set $t = t + 1$;
end while
Output global optimal position $g_{\text{best}}$;
End

Through the analysis in Section 4.1, the SVM model has better forecasting stability than ELM. However, in the early stage of prediction, the prediction effect of ELM is better than that of the SVM model. Therefore, this study proposes an ELM-BSASVM (extreme learning machine -bird swarm optimization support vector machine) combination model. The ELM–BSASVM combination model combines the ELM model and the SVM model to forecast the life of the battery.

From Figure 9, we can find that the ELM model has a good prediction effect on the first 80 samples. First, the ELM model was used to predict the first 80 samples. Then, the predicted value of ELM is used as the input of BSASVM(bird swarm optimization support vector machine)model, and the remaining samples are predicted by BSASVM model. Finally, the predicted values of BSASVM and ELM model are combined to form the overall predicted results. The ELM–BSASVM model has the characteristics of the good early fitting effect of the ELM model and also has the characteristics of high stability prediction of the SVM model. The evaluation process of ELM-BSASVM model is shown in Figure 11.

Finally, the life of the lithium-ion cell is forecasted by the ELM–BSASVM combination model. The data in Table 3 are used to test ELM–BSASVM. The test results are shown in Figure 12.

The prediction curves of the ELM–BSASVM model are closer to the actual value curves by comparing the forecasting curves in Figures 8, 9, and 12. In the early stage of prediction, the forecasting effect of ELM–BSASVM is obviously better than that of the SVM model. In the later stage of prediction, ELM–BSASVM model overcomes the disadvantage of poor forecasting stability of ELM.
So as to more intuitively compare the forecasting effects of the ELM, SVM, and ELM–BSASVM models, the RMSE and $R^2$ values of the three prediction models are shown in Figure 13.

Experiments 1 and 2 presented the ELM–BSASVM has the smallest RMSE value, and the ELM has the largest RMSE value. The $R^2$ value of ELM–BSASVM is similar to SVM, and the $R^2$ value of ELM is closest to 0. In Experiments 1 and 2, the ELM, SVM, and ELM–BSASVM models forecast the residual life values of the lithium-ion cell as shown in Table 4.

Experiments 1 and 2 presented the predicted values of the ELM model are 221 and 122. The AE of the ELM model is the largest. The forecasting effect of ELM model is poor by analyzing the forecasting curves of ELM in Figure 9. The predicted values of the ELM–BSASVM model are 214 and 114. The predicted remaining life of the

Figure 11. Evaluation process of ELM–BSASVM model. BSASVM: bird swarm optimization support vector machine; ELM: extreme learning machine; SVM: support vector machine.
ELM–BSASVM is closest to the failure value of the lithium-ion battery. For Experiment 1 and 2, the iteration curves of BSA algorithm are as shown in Figure 14.

For experiment 1 and 2, the iteration curves of BSA algorithm are as follows.

The comprehensive analysis of the prediction effects of the three models is as follows.

![Figure 12](image)

**Figure 12.** Prediction result of ELM–BSASVM model. (a) Test results of ELM–BSASVM model in experiment 1, (b) test errors of ELM–BSASVM model in experiment 1, (c) test results of ELM–BSASVM model in experiment 2, and (d) test errors of ELM–BSASVM model in experiment 2. BSASVM: bird swarm optimization support vector machine; ELM: extreme learning machine.

![Figure 13](image)

**Figure 13.** Analysis of RMSE and $R^2$ of three models. (a) Comparison of RMSE values of three models and (b) comparison of $R^2$ values of three models. BSASVM: bird swarm optimization support vector machine; ELM: extreme learning machine; RMSE: root mean square error; SVM: support vector machine.
Figure 14. The iteration curves of BSA algorithm. (a) The iteration curve of BSA algorithm for experiment 1 and (b) the iteration curve of BSA algorithm for experiment 2.

Table 4. Analysis of prediction model results.

| Experiment | Model       | Failure value | Predicted value | AE  | RMSE (%) | R²   |
|------------|-------------|---------------|-----------------|-----|----------|------|
| 1          | SVM         | 193           | 219             | 26  | 0.71     | 0.9951|
|            | ELM         | 221           | 28              | 2.51| 0.5488   |      |
|            | ELM–BSASVM  | 210           | 17              | 0.35| 0.9970   |      |
| 2          | SVM         | 93            | 118             | 25  | 0.63     | 0.9881|
|            | ELM         | 122           | 29              | 1.37| 0.6990   |      |
|            | ELM–BSASVM  | 96            | 3               | 0.23| 0.9855   |      |

AE: absolute error; BSASVM: bird swarm optimization support vector machine; ELM: extreme learning machine; RMSE: root mean square error; SVM: support vector machine.
In the two experiments, the RMSE values of SVM and ELM–BSASVM models fluctuate little, indicating that the prediction stability of the two models is good and two models have strong robustness. On the contrary, the RMSE value of the ELM model fluctuates greatly, and its prediction stability is poor. The RMSE value obtained in experiment 2 is 45.42% smaller than the RMSE value obtained in experiment 1, indicating that the robustness of the ELM model is weak. As the number of samples increases, the prediction error of the ELM model becomes smaller.

The RMSE value of ELM–BSASVM model is the smallest for both experiment 1 and experiment 2. For experiment 1, the RMSE value of ELM–BSASVM model is 50.7 and 86.05% smaller than that of SVM and ELM. And for experiment 2, the RMSE value of ELM–BSASVM model is 63.49 and 83.21% smaller than that of SVM and ELM.

For $R^2$ value, the fitting effect of SVM model and ELM–BSASVM model is similar. The $R^2$ value of both models is close to 1. The $R^2$ value of the ELM model is closer to 0. The fitting effect of prediction curve and the real curve is weak. The prediction result of ELM is getting worse and worse with the increase of test samples in Figure 9. Especially in the later stage, the ELM model can hardly predict the trend of lithium-ion battery capacity decay curve.

The forecasting effect of ELM–BSASVM model is the best by observing the data of Figures 8, 9, and 12, and comparing with the data in Table 4. The ELM–BSASVM model proposed in this study not only has the characteristics of high prediction stability of SVM model but also has the advantages of high pre-fitting accuracy of ELM model.

**Conclusions**

With more and more attention paid to the development and utilization of new energy in the world, as well as the continuous maturity of new energy power generation technology, the security of energy storage system is very important. Lithium battery is widely used in energy storage system because of its advantages. Therefore, the healthy state of lithium battery plays an important role in the safe and stable operation of energy storage system. As the energy battery ages, their health status directly affects the operation of the energy system. So the health status of energy battery needs to be assessed. So this study presents a hybrid model to predict the remaining life of lithium-ion cells. And the following important conclusions are obtained.

1. In this paper, different wavelet basis functions are used to denoise the original data. And it is found that the SNR values of the four wavelets are similar, but the MSE value of the Haar wavelet is 5.31e-28. The test results show that the Haar wavelet has the best denoising effect.
2. The remaining life of the lithium-ion cell is predicted by SVM and ELM models. The simulation results in Table 3 indicate that the SVM model has better forecasting stability than the ELM model. The robustness of the ELM model is poor. In the later stage, the ELM model cannot forecast the trend of cell capacity attenuation data. Through comparative analysis, it is found that in the early stage of prediction, the ELM model’s RMSE value is smaller than the RMSE value of the SVM. The $R^2$ values of the two models are around 0.9.
3. The prediction effect of the combined model is better than that of the single model. The RMSE value of the ELM–BSASVM model is minimal regardless of experiment 1.
or experiment 2. For experiment 1, the RMSE value of ELM–BSASVM model is 50.7 and 86.05% smaller than that of SVM and ELM. And for experiment 2, the RMSE value of ELM–BSASVM model is 63.49 and 83.21% smaller than that of SVM and ELM. For $R^2$ value, the SVM model and the ELM–BSASVM model have similar fitting effects, and the $R^2$ values of both models are close to 1. The robustness of the ELM–BSASVM model is strong.

4. Improving the health management level of lithium batteries plays a positive role in the development of energy storage system. And it can also promote the development and utilization of energy resources.

In this study, a hybrid model was used to predict the residual life of lithium batteries. However, this study still has limitations. The limitations of this study are as follows: (1) this study is aimed at a single cell rather than the entire battery pack; (2) the battery degradation data studied are not data obtained under actual operating conditions of energy storage system. Hence, the future study should evaluate the health status of energy storage system under actual operating conditions.

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