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State of health estimation for Li-ion battery using characteristic voltage intervals and genetic algorithm optimized back propagation neural network

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ABSTRACT

The accurate estimation of lithium-ion battery state of health (SOH) is important for the battery safety condition and range. However, in most cases, the operating conditions of lithium batteries are highly random. The data length of each cycle during the actual use of lithium-ion batteries is highly random and does not satisfy the input conditions of existing SOH estimation methods. To deal with the randomness of battery data, this paper proposes a SOH estimation scheme based on BP neural network optimized by a genetic algorithm (GA-BP) and fixed characteristic voltage interval. The method selects the effective charging cycle data on random length data through fixed characteristic voltage interval as the model training set, constructs 3 different feature parameters on this training set, and trains the GA-BP model with it to achieve SOH estimation on random length data. Experiments with the Monte Carlo method on 2 publicly available datasets validated the accuracy of the method at different levels of randomization.

1. Introduction

With a low self-discharge rate, long cycle life, and high energy density, lithium-ion batteries have become a major energy storage component in electrification fields such as electric vehicles, microgrids, and other electronic products [1]. Lithium-ion batteries continue to age with use, leading to a decline in usable battery capacity and safety issues [2]. To ensure the safe and stable operation of the battery system, it is important to accurately estimate the state of health (SOH) of the battery at the current moment. At present, the evaluation index of SOH has not been unified in academic circles, which can be roughly divided into four aspects: capacity, internal resistance, power, and the number of charge/discharge cycles [3–5]. The current mainstream SOH definition is from the capacity perspective, i.e., the ratio of the current maximum available capacity to the initial maximum capacity as the SOH evaluation index [6]. The formula is defined as follows:

$$SOH = \frac{C_C}{C_I} * 100\% \tag{1}$$

where C_C indicates the maximum available capacity of the current cycle and C_I indicates the maximum available capacity of the initial cycle. The initial SOH of the battery is 100 %, when the SOH of the battery declines to 70 % or 80 % or less, the battery is usually considered to have reached its end of life [7].

Since the SOH of the battery could not be measured directly, the researchers achieved an indirect estimation of SOH by other directly measured electrical quantities such as voltage and current. The current SOH estimation methods are divided into two main types: model-based methods and data-driven methods [8]. The model-based approach determines the relationship between battery capacity and the number of cycles (or throughput capacity) by identifying the model parameters [9]. The model-based approach contains an electrochemical model an equivalent circuit model. The electrochemical model is a mathematical method to simulate the internal working mechanism of the battery, to build an accurate battery model [10]. However, the partial differential equations deployed by this method lead to excessive computational effort and require electrochemical impedance spectroscopy to determine the model parameters, making it difficult to apply online [11]. To solve the problem of the excessive complexity of electrochemical models, Chun et al. [12] transferred electrochemical knowledge to a small-sized inverted bottleneck network (IBN) to accurately estimate the capacities of different aging states in a short computational time. The equivalent circuit model uses nonlinear circuit elements to construct the internal

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working mechanism of the equivalent circuit cell, and its parameter complexity is much lower than that of the electrochemical model, which also leads to its limited model accuracy [13]. Further, the parameter identification of the equivalent circuit model requires a pulse discharge process, which is difficult to implement for online applications.

The data-driven approach has the advantage of flexibility by establishing a nonlinear mapping relationship between the feature parameters and the estimated values without relying on a model [14] and has now gained wide interest from all walks of life. A large number of scholars have currently used machine learning methods applied to battery SOH estimation, such as neural networks [15], Gaussian filter [16], support vector machines [17], etc. The feature extraction method is the key to the machine learning method and directly affects the accuracy of the final estimation results. The feature extraction methods can be divided into manual extraction and automatic extraction. The manual extraction feature approach requires an artificially constructed metric that adequately characterizes the battery capacity decline mechanism, such as capacity increment. To reduce the capacity increment curve error, Li used a Gaussian filter to obtain a smoother capacity increment curve, based on which the extracted features correlate better with the capacity recession mechanism [18].

The automatic feature extraction method does not require humans to construct features, directly input the electrical quantity and SOH value of each cycle, and automatically learn and extract features through a neural network to achieve end-to-end SOH estimation [19]. Kim et al. proposed a new SOH estimation scheme based on a neural network, which can use voltage and current data in a short time to estimate SOH value, to achieve the effect of reducing the number of Reference Performance test (RPT) [20]. Han used a hybrid neural network to capture the hierarchical features and temporal information of the battery data, combined with a Bayesian optimized neural network structure to achieve an end-to-end estimation of the battery SOH and remaining useful life(RUL) [21]. The automatic feature extraction method has good generalization performance for different battery types, but the input data requirements are more stringent, requiring the input of a complete charging curve.

In practice, it is impossible to control the data length of each cycle, i.e. the battery will not always be fully charged and then discharged to the cut-off voltage. Therefore, the battery usage data with random data length is not suitable for current automatic feature extraction methods.

Therefore, to solve the problem of accurate SOH estimation of lithium-ion batteries with random data length, this paper proposes a SOH estimation method adapted to the random data length. The method can obtain discontinuous service cycle data by fixed voltage characteristic interval and sparse input data. The neural network model was trained with discontinuous cyclic data, and the optimal parameters of SOH estimation were found by a genetic algorithm. Finally, Monte Carlo simulation results on two open data sets show that the proposed method can achieve more accurate SOH estimation when the voltage coverage is 50 % or above.

This paper is structured as follows: Section 2 describes the dataset and feature parameter extraction methods. Section 3 presents the model of the BP neural network optimized by a genetic algorithm and the specific process of this model to estimate SOH. In Section 4, Monte Carlo-based stochastic simulation experiments are conducted to verify the estimation effect of the proposed method in this paper under different voltage coverage. A summary of the work done in this paper and an outlook on future work are presented in Section 5.

2. Features extraction

Directly measured battery usage data can reflect the battery degradation to some extent, for example, the charging voltage curve will show regular changes with the number of cycles, but it is difficult to directly characterize the SOH of the battery. Based on the a priori knowledge related to the battery degradation mechanism, the feature parameters highly correlated with the battery SOH can be extracted from multiple dimensions, and the combination of regression algorithms can achieve an accurate estimation of SOH.

Table 1
Battery specific parameters.

Battery	Sampling interval (s)	Rated capacity (Ah)	Discharge current (V)	Temperature (°C)
C1	1	0.74	1.48	40
C2	1	0.74	1.48	40
B5	30	2.1	2	24
B6	30	2.1	2	24

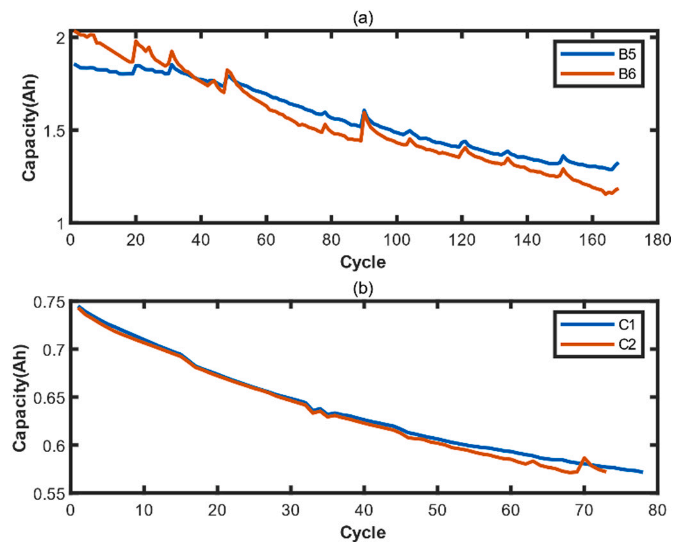

Fig. 1. Battery capacity decline curve.
(a) Battery B5, B6 in NASA dataset (b) Battery C1, C2 in Oxford dataset.

2.1. Battery aging data

The rate of capacity degradation will vary for different battery types and different charging and discharging rules. NASA battery random use dataset [22] and the Oxford battery aging dataset [23] were used in this paper. The above data sets record the battery charge voltage data and the battery capacity is measured by the ampere-time integration method during the discharge phase after every cycle to obtain the actual SOH.

The battery used in the NASA Li-ion random data set is an LG Chem 18650 cylindrical battery with a rated capacity of 2.1 Ah and a conventional operating voltage range of 3.2 to 4.2 V. A total of 28 identical Li-ion batteries were tested in this data set, and the batteries were divided into seven groups according to different experimental conditions, with the minimum capacity decaying to 0.80 Ah. Each group of experiments uses different random working conditions during discharge. The Oxford University battery aging dataset uses 8 Kokam lithium-ion cobalt-acid pouch batteries, which have a rated capacity of 740 mAh. Unlike the NASA random aging dataset, the Oxford datasets were obtained by repeatedly discharging and recharging the Li-ion battery at a constant current of 2C (1.48A) using ARTEMIS urban driving conditions at a constant ambient temperature of 40 °C. During charging, the voltage was collected at a frequency of 1 Hz. In this paper, cells B5 and B6 were selected from the NASA dataset, and cells Cell1 and Cell2 were selected from the Oxford dataset and are marked as C1 and C2. Specific information about the above batteries is shown in Table 1, and the decline curve of the batteries is shown in Fig. 1.

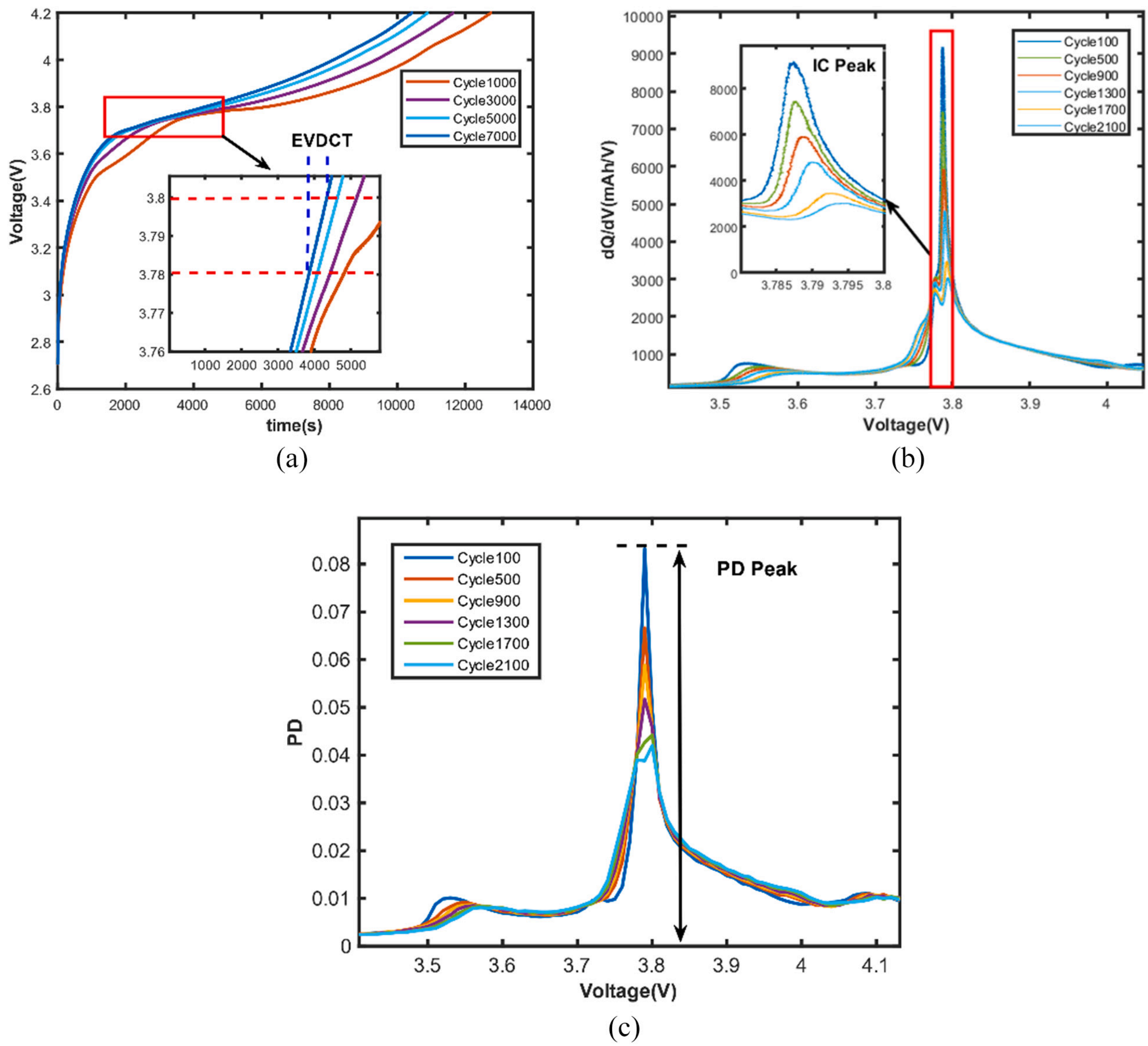

Fig. 2. Three characteristic parameters based on fixed charging voltage intervals.
(a) The charging curve of battery C1.
(b) The capacity increment curves of battery C1.
(c) The voltage probability density curves of battery C1.

2.2. Features extraction

The extraction method of feature parameters affects the final effect of battery SOH estimation. Most of the current methods for SOH estimation to extract feature parameters are based on the combination or differential calculation of direct measurement data such as voltage, current, and temperature. The charge voltage curve of Li-ion batteries changes with the number of cycles. As shown in Fig. 2(a), taking the Oxford University battery data set as an example, the charging voltage curve of Li-ion battery is characterized by steep curves at the beginning and end stages, while the voltage curve in the middle state is flatter and is called the plateau voltage. As the number of cycles increases, the duration of the plateau voltage decreases. Based on this property, Equal voltage difference charging time (EVDCT) was used as a feature parameter for estimating SOH [24]. As shown in Fig. 2(a), the charging time decreases with the number of cycles for each fixed voltage difference, a characteristic consistent with the trend of battery capacity decline. The incremental capacity analysis (ICA) based method describes the correspondence between battery capacity decline and charge voltage variation. The ICA method is used to highlight the capacity increments corresponding to different voltage intervals of the charging process by calculating the differential dQ/dV of the capacity Q concerning the voltage V. Fig. 2(b) shows that the highest peak of the ICA curve decreases as the number of cycles increases. To a certain extent, the highest peak value of ICA can roughly reflect the battery capacity decline. As in Fig. 2(c), the probability density (PD) analysis method analyzes the association between the voltage profile and the capacity recession by counting the probability density of the occurrence of each voltage value [25]. There is also a correlation between the highest peak of the PD curve and the capacity decline. As shown in Fig. 2, the voltage data required for feature parameter extraction in the Oxford dataset is concentrated in the 3.78 V–3.8 V interval. This means that the complete charging voltage data is not required to estimate the battery SOH, but only a smaller voltage interval is required. Considering that more voltage data are required for capacity incremental curve plotting, 3.75 V–3.85 V is used as the characteristic voltage interval.

The correlation between the above characteristic parameters and the battery capacity decline was analyzed using Pearson's correlation

Table 2
Correlation of each feature with battery capacity.

Features	Cell1	Cell2	B5	B6
ICPeak	0.8829	0.9016	0.9953	0.9802
PDPeak	0.9247	0.9212	0.9244	0.9085
EVDCT	0.8666	0.9934	0.9915	0.9941

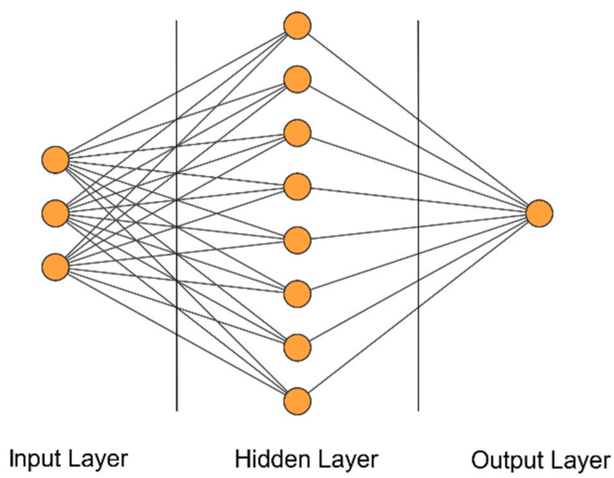

Fig. 3. Back propagation neural network structure.

coefficient. The Pearson correlation coefficient is calculated as follows:

$$\rho_{X,Y} = \frac{\sum_{i=1}^{N}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{N}(X_i - \overline{X})^2}\sqrt{\sum_{i=1}^{N}(Y_i - \overline{Y})^2}} \tag{2}$$

where X_i, $\overline{X}$ correspond to the characteristic parameters and its average value, Y_i, $\overline{Y}$ the cell capacity and its average value, and N is the data length. The correlation coefficients of the characteristic parameters and the capacity are shown in Table 2. The results show that all three feature parameters in this paper have a significant positive correlation with the capacity decline trend of the battery.

3. Method

3.1. Back propagation neural network

The artificial neural network (ANN) can accurately approximate any nonlinear function and has good system learning ability, while the ANN has very good robustness, which can effectively solve the complex mapping relationship between battery SOH and measurement parameters and stability problems. Backpropagation (BP) network is a neural network with an error back propagation link. The structure is shown in Fig. 3. The input signal reaches the hidden layer through the input layer, and then reaches the output layer after processing. When the difference between the output result and the desired result is large, it enters the backpropagation stage of the error, and then the error between the

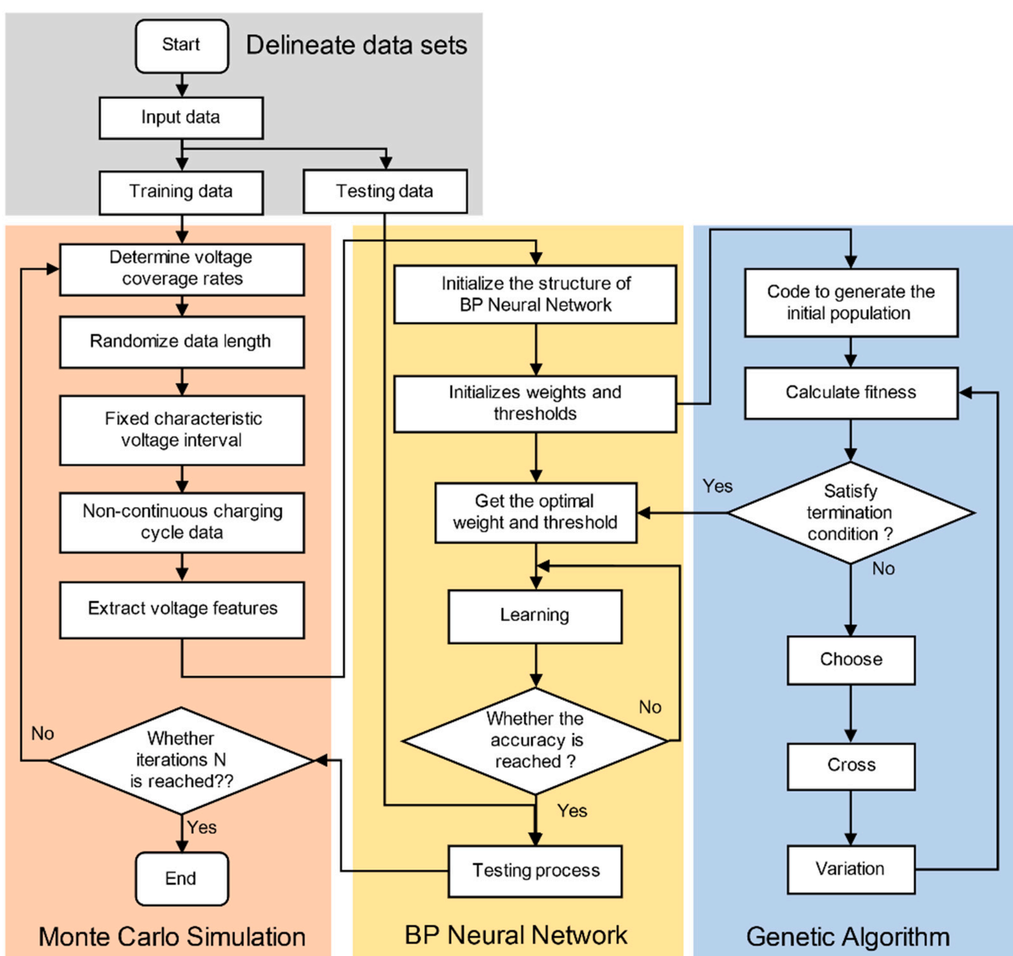

Fig. 4. Battery SOH estimation flow chart.

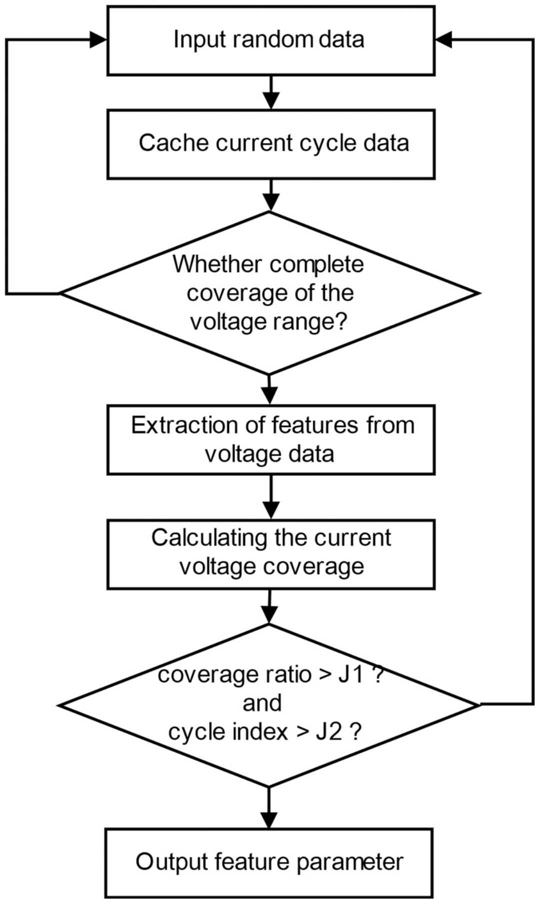

Fig. 5. Feature parameter extraction flow chart.

output result and the desired result is used as the basis to constantly adjust the weights and thresholds so that the predicted output value of the network is constantly close to the desired value.

3.2. Genetic algorithm

Although BP neural networks are developing rapidly, the relevant theories are still immature, and there are problems of difficulty in determining the optimal parameters and slow convergence speed in practical applications. To address this, a genetic algorithm (GA) is used to find the optimal weights and thresholds of the BP neural network, to improve the accuracy and convergence speed of the BP neural network in estimating SOH.

A genetic algorithm is a method that simulates the natural evolutionary process to search for the optimal solution. It draws on natural selection and natural genetic mechanisms in biology and was proposed by Professor J.H. Holland at the University of Mississippi in the 1960s. It is based on the Darwinian evolutionary principle of survival of the fittest and uses the basic operations of genetics repeatedly for the population containing feasible solutions to continuously generate new populations so that the population evolves continuously. At the same time, the global parallel search technique is used to search for the optimal individuals of the optimized population to find the optimal solution that satisfies the requirements.

3.3. Battery SOH estimation process

As shown in Fig. 4, the lithium-ion battery SOH estimation model is divided into four parts: Delineating data sets, Monte Carlo Simulation, BP Neural Network, and Genetic Algorithm.

3.3.1. Delineate data sets

The actual battery operation data, including voltage, current, and capacity, input to the model are divided into a training set and a test set according to a 50 % ratio. To ensure that SOH estimation is achieved before the battery capacity declines to 70 %, the actual division ratio is adjusted according to the battery decline rate.

3.3.2. Monte Carlo simulation

Random lengths of voltage data are simulated according to a set voltage coverage rate. Based on the concept of voltage characteristic interval proposed in Section 2.2, the percentage of data containing the interval 3.75 V–3.85 V is identified as the voltage coverage rate. The mathematical form is as follows.

$$Coverage\ rate = \frac{\sum_{i=1}^{N} f(x)}{N} \tag{3}$$

$$f(x) = \begin{cases} 1, & T \in N_i \\ 0, & T \notin N_i \end{cases} \tag{4}$$

where N is the number of battery cycles, T is the characteristic voltage interval, and N_i is the data of the current cycle under random simulation conditions. The voltage coverage reflects the usage data of the battery in different conditions. The random data are filtered according to the feature interval to find the effective usage period, and based on this, the feature parameters are extracted and used as the input to the BP neural network. The flow of feature parameter extraction on random data is shown in Fig. 5. First, it is necessary to determine whether the data under the current cycle meets the requirements for feature extraction. Then, the cache performs regular voltage feature extraction on the data satisfying the requirement. Finally, the feature parameters are output when the number of cycles and voltage coverage reaches the threshold J1 and J2, respectively. Using the voltage coverage method to filter random data eliminates the need to double-compute all cycles, and features are extracted for those cycles that meet the conditions. When the data does not meet the voltage coverage conditions, the cache data can be released directly, which reduces a lot of data calculation pressure. The process of random simulation is repeated several times to verify the robustness of the model.

3.3.3. BP neural network

The feature parameters extracted in the previous section are fed into the network to control the topology of the network and the optimal weights and thresholds obtained by GA optimization so that the neural network learns the mapping relationship between the feature parameters and SOH. The structure of the BP neural network contains 3 neurons for the input, 6 neurons for the hidden layer, and 1 neuron for the output layer. The single-layer neural network can reduce the computational pressure of the battery management system to the greatest extent. At the same time, the neural network training needs to meet the two limiting conditions, so there is enough time for the BMS training model. In the estimation of SOH, voltage is also required to meet the limiting condition, so this scheme is feasible in the application of BMS.

3.3.4. Genetic algorithm

The flow chart of the GA optimized BP network is shown in Fig. 4. The initial population individuals are randomly generated, and each individual contains the weights and thresholds of the BP neural network, and the population individuals are used as the BP neural network parameters before the BP neural network training, and the fitness of the population individuals is calculated by the error of the BP neural network output results. The optimal solution is inherited from the set of random solutions, and the inherited optimal individuals are used as the initial weights and thresholds of the BP neural network structure, and then the BP algorithm quickly adjusts the weights and thresholds in the

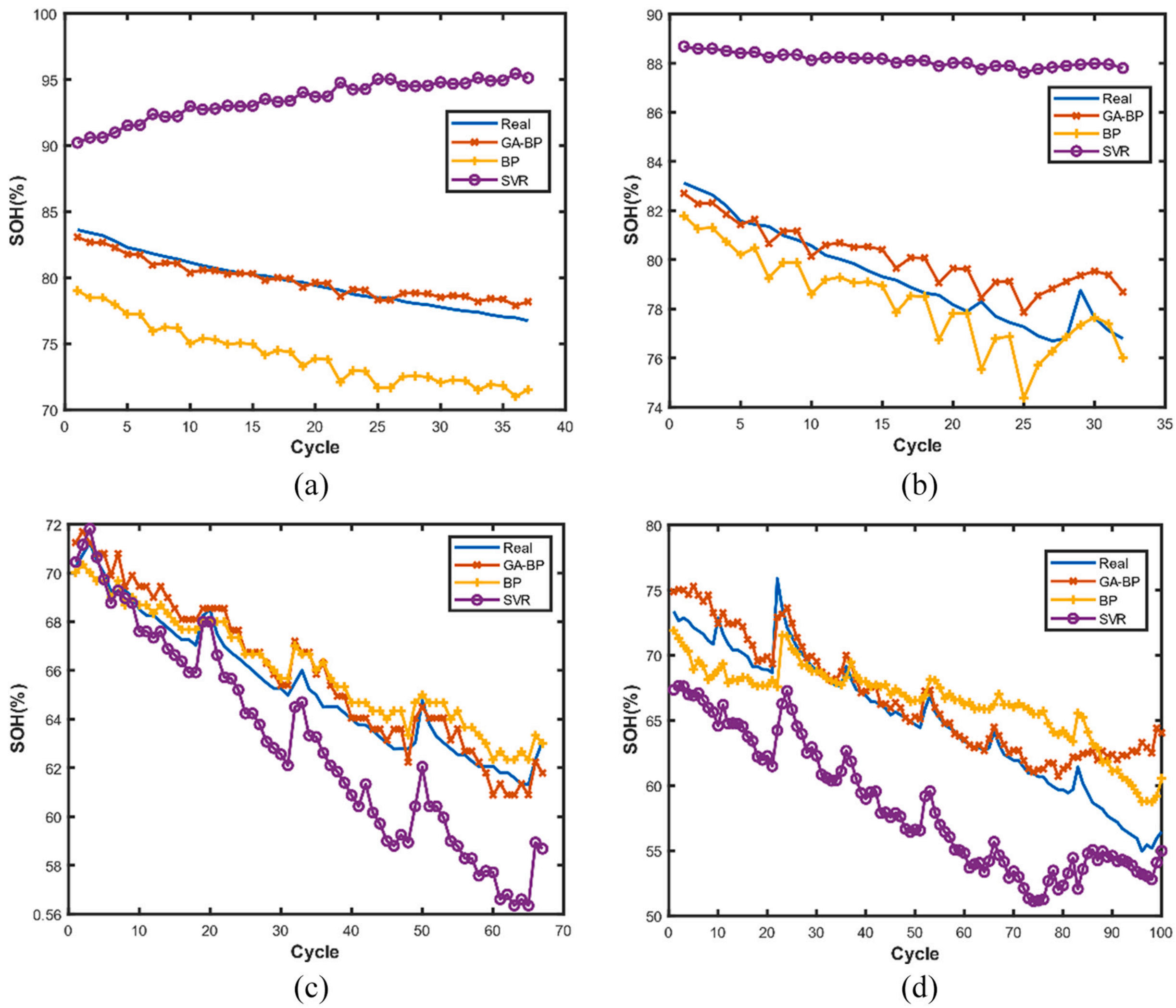

Fig. 6. The estimation results of three different methods on the battery SOH. (a) batteryC1 (b) batteryC2 (c) batteryB5 (d) batteryB6.

negative gradient direction to achieve the global optimal point, which ensures that the network converges to the global optimal point and also improves the speed of convergence.

4. Results and analysis

4.1. Evaluation metrics

The mean absolute error (RMSE) and max error (MAE) are used as evaluation metrics to quantitatively assess the accuracy of the SOH estimation algorithm proposed in this paper. The formulas are shown as follows.

$$RMSE = \frac{1}{n}\sum_{i=1}^{m}(y_i - \widehat{y}_i)^2 \tag{5}$$

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|y_i - \widehat{y}_i| \tag{6}$$

4.2. Experimental results and analysis

Real battery usage data, the length of which will not always be fixed, is simulated using a random simulation method. The rules for random simulation are set in proportion to the voltage data covering the

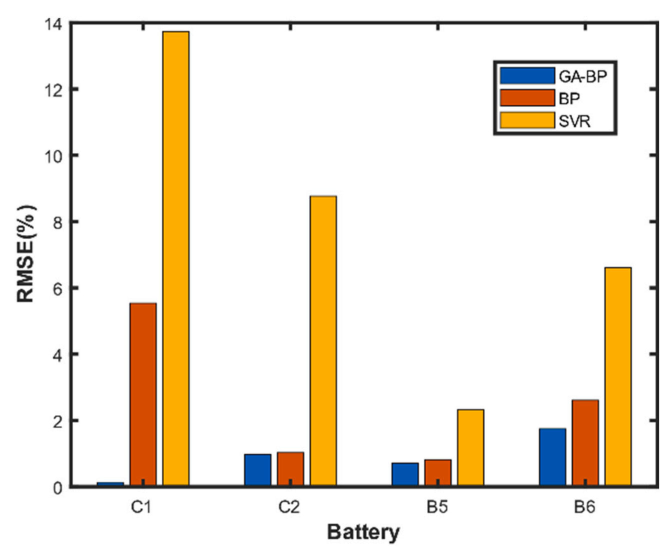

Fig. 7. RMSE metrics for three different methods on four cells SOH.

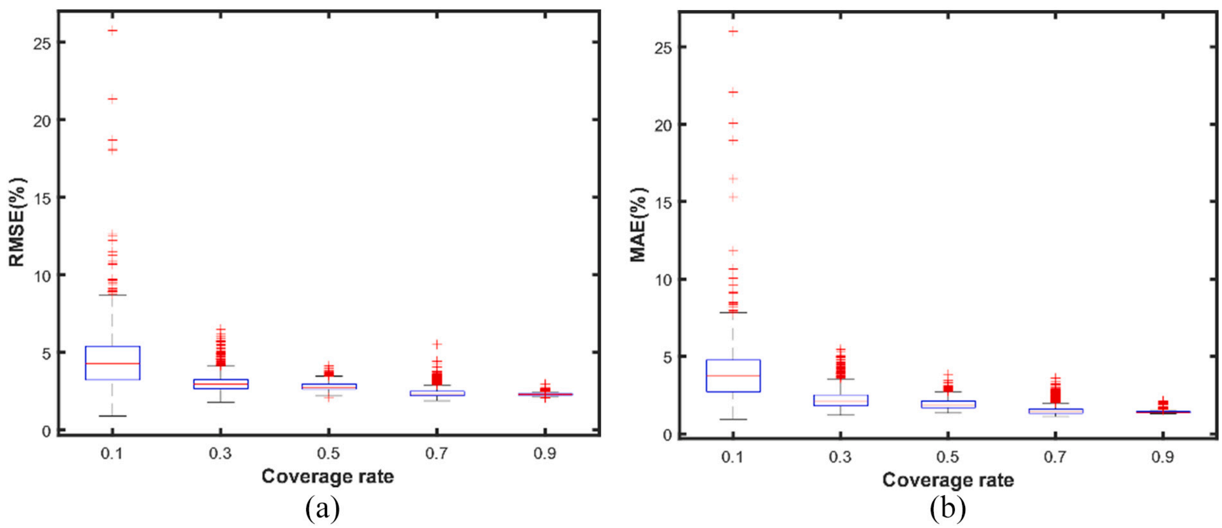

Fig. 8. Box plot of the estimated effect of GA-BP model with different voltage coverage.
(a) RMSE metrics (b) MAE metrics.

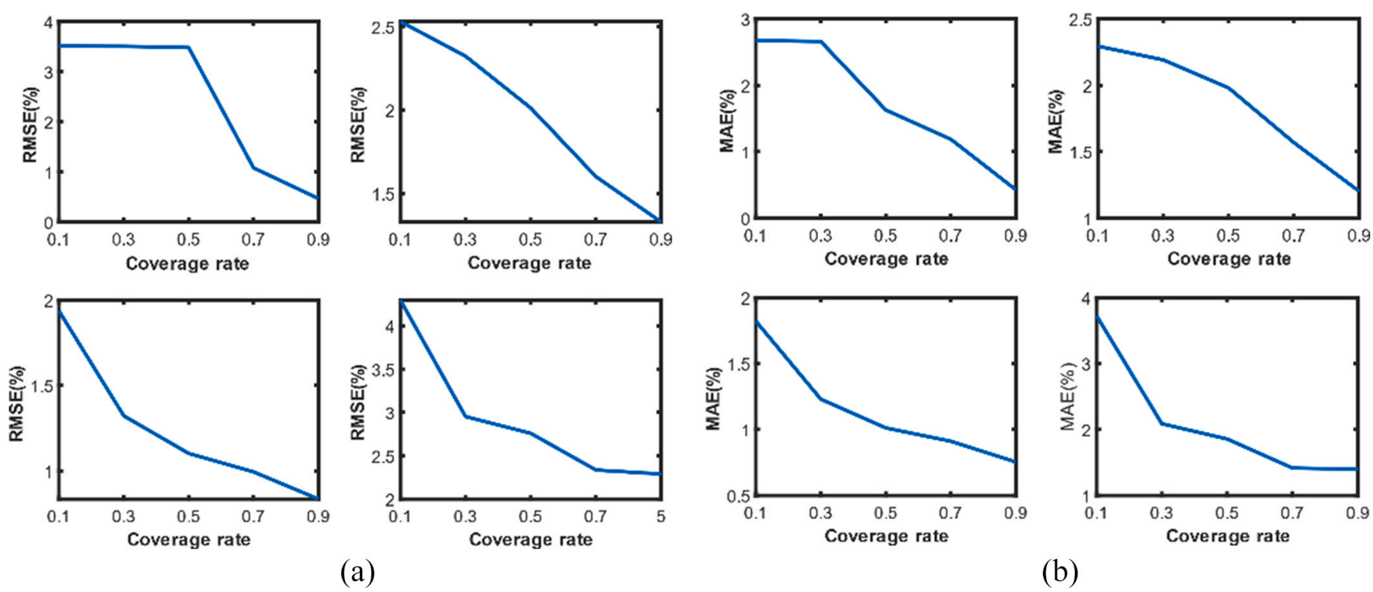

Fig. 9. Variation of the median estimation error of GA-BP model with data coverage.
(a) RMSE metrics (b) MAE metrics.

characteristic interval. To verify the estimation accuracy of the GA-BP neural network model under ideal conditions, this paper conducts comparative experiments using the traditional support vector machine regression algorithm SVR, and a BP neural network not optimized using a genetic algorithm. Since the decline rate of C1 and C2 cells in the Oxford dataset is comparable, the first 50 % of the cyclic data of C1 and C2 cells are taken as the training set and the last 50 % of the cyclic data are taken as the test set. The first 100 cycles of the B5 battery and the first 68 cycles of the B6 battery were taken as the training set, and the remaining data were used as the test set to verify the accuracy of SOH estimation.

The estimation results of the three models under different cells are shown in Fig. 6. The estimation results of SVR deviated from the true SOH, the estimation results of the BP neural network had the smallest estimation error in the data of C2 and B5 cells, and the estimation results of BP neural network optimized by the genetic algorithm were the best. Fig. 7 shows the estimation errors of the three algorithms on different battery data with the error metric RMSE. The estimation errors of the three methods are lower on B5 and B6 cells than on C1 and C2 cells because the data period of B5 and B6 cells is longer and the training set is larger. The overall estimation performance of the three methods on the B5 cell data is better than that of the B6 cell, also because of the larger amount of data in the training set used for B5.

To verify the estimation performance of the GA-BP model under real data length, the data coverage was adjusted to simulate real battery usage data by the Monte Carlo simulation method, and the experiment was repeated 1000 times at different voltage coverage, respectively. The data coverage includes 0.1, 0.3, 0.5, 0.7, and 0.9, with higher coverage indicating more effective charging cycles. As shown in Fig. 8, the distribution of SOH estimation error is shrinking and the median error is decreasing as the data coverage gradually increases in the B6 battery data. It is noteworthy that the model has been able to accurately estimate the battery SOH at a voltage coverage of 0.3 with an RMSE index of 2.952 % and an MAE index of 2.087 %. As the coverage rate increases, the estimation accuracy of the model will further improve and the robustness of the model will be stronger.

Fig. 9 shows the variation of the median estimation error of the GA-BP model with the data coverage. In different battery data, the estimation error decreases with increasing coverage, indicating that the GA-BP model is underfitting for the training effect, and the more training data are available, the higher the estimation accuracy of the model. It is worth noting that the model can get more accurate estimation results if the proportion of intervals with real data covering the characteristic voltage exceeds 0.5.

5. Summary

In this paper, to address the problem that the SOH of lithium-ion batteries is difficult to be estimated directly under random charging data, three feature parameters that can characterize battery degradation are extracted in the characteristic voltage interval, and a genetic algorithm is used to optimize a BP neural network for SOH estimation. Stochastic data of the battery under different coverage are simulated by the Monte Carlo method, and the estimation effect under different data coverage is verified using this data. The results show that the model can achieve a more accurate SOH estimation of lithium batteries under random charging data, as long as the ratio of data coverage feature intervals reaches 0.5 and above. In the future, we will conduct experiments to simulate the stochastic battery operating conditions and investigate a more accurate and generalized SOH estimation method.

CRediT authorship contribution statement

Zhang Fan: Supervision, Writing – review & editing. **Xing Zi-xuan:** Writing – original draft, Methodology, Conceptualization, Software, Validation, Formal analysis, Writing – review & editing. **Wu Ming-hu:** Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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