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Research on state-of-charge Estimation of Lithium-ion Batteries Based on Improved Sparrow Search Algorithm-BP Neural Network

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As one of the key parameters of the battery management system (BMS), the accurate estimation of the state of charge (SOC) of lithium-ion batteries is of great significance to the development of electric vehicles. Aiming at the problem that the BP neural network is easy to fall into the local optimum, taking lithium-ion batteries as the research object, a lithium-ion battery SOC estimation method based on the Improved Sparrow Search Algorithm (ISSA) optimized BP neural network is proposed. In order to improve the estimation accuracy, the global optimal solution of the previous generation is introduced into the discoverer's position update strategy, and the simulation experiment is carried out in MATLAB, combined with the test data for analysis. The experimental results show that the improved sparrow search algorithm can better optimize the BP neural network to estimate the state of charge of the lithium-ion battery, and the average error is controlled within 1%. The ISSA-BP model is compared with other models to verify the rationality and accuracy of the model, and provide a reliable basis for monitoring the status of other important batteries.

Keywords: Lithium-ion battery; State of charge; BP neural network; Improved sparrow search algorithm

1. INTRODUCTION

With the rapid development of society, the energy crisis and environmental pollution have become two major problems facing every country in the world today[1]. As new energy has many advantages of sustainability and environmental protection, besides, serious environmental pollution and intense consumption of fossil fuels force people to place the research and development of new energy in an increasingly important position[2, 3]. As an emerging industry in recent years, new energy vehicles have developed rapidly. Power battery technology is not only the core of current research in the electric vehicle industry but also the main factor restricting the performance of electric vehicles[4]. Considering performance and cost conditions, lithium-ion batteries have become the first choice for batteries of new energy vehicles by virtue of their high energy density, high cell voltage, long cycle life, and high output power[5, 6]. They are widely used in portable equipment and industrial applications. As a result, the health status and real-time monitoring accuracy of lithium-ion batteries have attracted more and more attention[7]. The Battery Management System is the core of the power battery. It is responsible for controlling the charging and discharging of the battery and realizing functions such as battery state estimation. It can timely and accurately monitor the battery to ensure the safe, efficient, and stable operation of the power battery[8]. As one of the main monitoring parameters in BMS, SOC is the prerequisite for accurately estimating the peak capacity of the battery, which can greatly improve the power distribution efficiency in the energy control strategy[9]. However, the SOC cannot be measured directly, and it can only be obtained indirectly through the external characteristics of the lithium-ion battery (working current, voltage, etc.)[10, 11]. In addition, the lithium-ion battery is a highly time-varying nonlinear system. Due to differences in battery materials and processes, and different industrial conditions, its dynamic characteristics are unstable[12-14]. If the lithium-ion battery is overcharged or over-discharged, it will lead to inaccurate SOC estimation, which will affect the service life of the battery and reduce the power performance of the battery[15, 16]. Therefore, how to estimate the SOC efficiently and accurately has become an issue of general concern and research in the industry.

So far, the estimation methods for lithium-ion battery SOC mainly include ampere-hour integration method, open-circuit voltage method, Kalman filter method, discharge test method, and neural network method[17]. The principle of the ampere-hour integration method is to detect the current of the battery during the charging and discharging process in real-time. Calculate the changed power consumption of the battery by calculating the integral of the current and the charge and discharge time during the monitoring period, and the difference between the initial SOC and the changed SOC is the remaining SOC[18]. However, the ampere-hour integration method only records the power in and out of the battery from the outside and ignores the internal state changes. If the measured current result is inaccurate, the SOC calculation error will continue to accumulate. In addition, this method needs to be calibrated regularly[19]. the principle of the open-circuit voltage method[20] is to leave the battery for a long time. Under this condition, the open-circuit voltage can be considered as the terminal voltage of the battery. The approximate function relationship between the open-circuit voltage and the SOC can be obtained, and the SOC can be estimated by measuring the open-circuit voltage in the resting state. However, the open-circuit voltage method requires the battery to be fully allowed to stand before the test, and the electric vehicle starts frequently, the open-circuit voltage is difficult to stabilize in a short time, and cannot meet the real-time estimation of SOC. The principle of the Kalman filtering method[21] is to estimate the SOC of the lithium-ion battery by collecting real-time voltage, current, temperature, and other variables, taking the SOC and polarization voltage as the state variables of the system, and measuring the terminal voltage as the observed variable of the system[22]. The core idea is to make the best estimate of the minimum variance of the variable. However, although the Kalman filtering method has high prediction accuracy and good applicability, the model is quite complex, computationally intensive, and time-consuming[23]. The principle of the discharge test method is to carry out constant current discharge experiments on a lithium-ion battery[24]. The product of discharge current and discharge time is the residual power. However, the discharge test method has strict test conditions. It requires constant current and accurate measurement. Therefore, it is often carried out in a stable and reliable ideal environment, and is mostly limited to the data measured under laboratory conditions[25]. The neural network[26] is a mathematical algorithm for distributed parallel information processing. According to the complexity of the system, the neural network realizes the processing and exploration of data by adjusting the relationship between a large number of internal nodes. The neural network method can map out the internal laws between input and output well through the learning of training samples. Among them, BP neural network, as the most widely used artificial neural network model, has a non-linear data structure. In view of the non-linear characteristics of the battery model itself, the BP neural network can better deal with the problem of SOC estimation of lithium-ion batteries[27-29].

Although BP neural network has strong nonlinear mapping ability, it also has problems such as slow convergence speed and easy to fall into a local minimum[30, 31]. At present, genetic algorithm[32, 33], particle swarm algorithm[34], and ant colony algorithm[35] are also used to optimize the initial weight and threshold of the BP neural network. Although the convergence speed has been improved, it is still easy to fall into the local optimal solution. Sparrow Search Algorithm is a novel population optimization algorithm. It is verified by 19 standard test functions that the SSA algorithm is superior to existing algorithms in terms of convergence accuracy, convergence speed, and avoiding local optimal solutions[36, 37].

Based on this, this paper uses the ISSA-BP neural network model to estimate the SOC of lithium-ion batteries. The model introduces the optimal solution of the previous generation in the iterative process to adjust the position update strategy of the sparrow, which improves the global optimization and search capabilities. Comparing the model with BP and SSA-BP, the result shows the feasibility and rationality of the improvement. Comparing this model with other models, the results verify that the ISSA-BP model is more superior in estimating the SOC of lithium-ion batteries.

2. MATHEMATICAL ANALYSIS

2.1. BP neural network

The SOC estimation model of the lithium-ion batteries established in this paper is based on the BP neural network using the sparrow search algorithm to optimize the final estimation results. The structure of the BP neural network is set to 2-8-1. Before using BP neural network for estimation, the network must be trained first, so that the network has associative memory and prediction capabilities. In this model, the current and voltage of the lithium-ion battery are used as input, and the SOC is used as output. The BP neural network training process is shown in Figure 1.

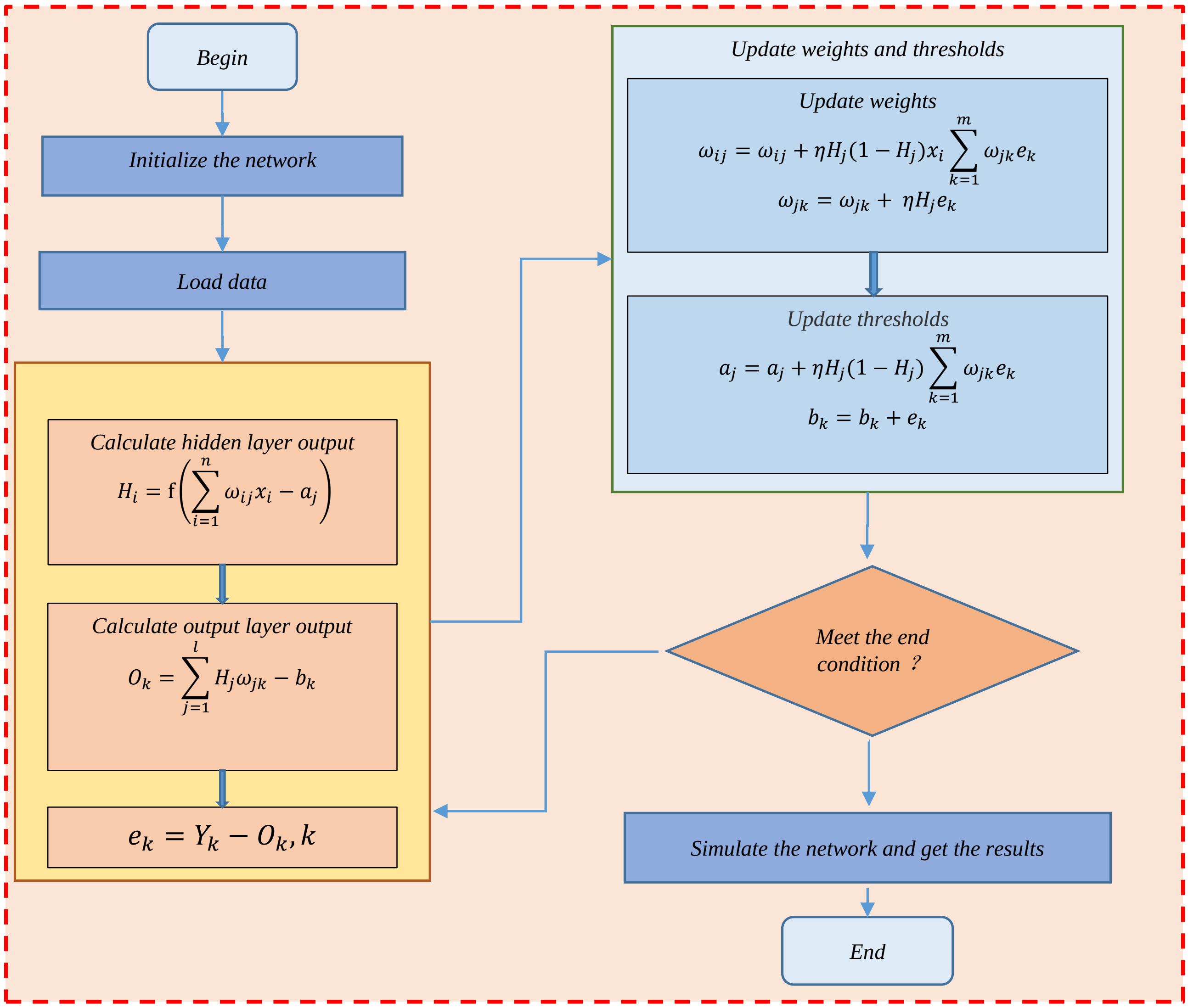


Figure 1. BP neural network training implementation process diagram

The training process shown in Figure 1 is: ①determine the basic structure of the BP neural network and initialize the hyperparameters of the network; ②import the experimental training data obtained in the two working conditions of DST and BBDST to train the network and calculate the output error; ③update the weight and threshold of the network to determine whether the termination conditions are met. If the termination conditions are met, the simulated network gets the output result. Otherwise, return to the previous step to recalculate the output error[38].

2.2. Sparrow search algorithm

The sparrow search algorithm is a kind of population intelligence optimization algorithm inspired by the foraging behavior and anti-predation behavior of sparrows. The sparrow search algorithm mainly simulates the foraging process of sparrows, which is a kind of discoverer-follower model, and also superimposes the detection and early warning mechanism. The core of the algorithm is to realize optimization by taking advantage of the sparrow's behavior of constantly adjusting and updating its position when foraging and avoiding danger. In this algorithm, the discoverers with better fitness value will get food first in the search process. In addition, because the discoverers are responsible for finding food for the entire sparrow population and providing foraging directions for all followers, the discoverers can obtain a larger foraging search range than the followers. Besides, some followers will always monitor the discoverers during the foraging process, fight for food with the discoverers or forage around the discoverers. When the entire population is threatened by predators or is aware of the danger, it will exhibit anti-predation behavior. The sparrows in the periphery of the population need to constantly adjust their positions to obtain a better position. At the same time, the sparrows in the center of the population will approach their neighbors to reduce their danger zone.

Each sparrow has one attribute and three possible behaviors. The attribute refers to the position, which represents the position of the food it finds. The three possible behaviors are: ①as a discoverer, continue to search for food; ②as a follower, following a discoverer for food; ③as a vigilant to watch out for reconnaissance, and give up food when in danger.

Assuming that the sparrow population X is composed of n sparrows, the corresponding fitness function value is represented by F_x. Its mathematical expression is shown in Eq. (1).

$$\begin{cases} X = \begin{bmatrix} x_1^1 & x_1^2 & \dots & x_1^d \\ x_2^1 & x_2^2 & \dots & x_2^d \\ \dots & \dots & \dots & \dots \\ x_n^1 & x_n^2 & \dots & x_n^d \end{bmatrix} \\ F_x = \begin{bmatrix} f[x_1^1 & x_1^2 & \dots & x_1^d] \\ f[x_2^1 & x_2^2 & \dots & x_2^d] \\ \dots & \dots & \dots & \dots \\ f[x_n^1 & x_n^2 & \dots & x_n^d] \end{bmatrix} \end{cases} \tag{1}$$

Among them, d represents the dimension of the problem to be optimized. According to the sequence of the process, the sparrow population is divided into two parts: the discoverers and the followers. During each iteration, the position update description of each discoverer is shown in Eq. (2).

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^t \cdot \exp\left(\dfrac{-i}{\alpha \cdot iter_{max}}\right) & if\ R_2 < ST \\ X_{i,j}^t + Q \cdot L & if\ R_2 \geq ST \end{cases} \tag{2}$$

Among them, $X_{i,j}^t$ represents the position of the i_{th} sparrow in the j_{th} dimension of the t-generation population. α is a random number of [0,1], $iter_{max}$ is the maximum number of iterations, and Q is a random number that obeys normal distribution. L $(1 \times d)$ is a matrix with all 1 element, R_2 represents the alarm value and $R_2 \in [0,1]$, ST stands for the alarm threshold, and $ST \in [0.5,1]$. When $R_2 < ST$, the sparrow is temporarily in no danger, and the discoverers start to search for food. Otherwise, the population needs to be transferred to a safe area. Followers look for food by monitoring and following the discoverer with the highest adaptability. The position update method is shown in Eq. (3).

$$X_{i,j}^{t+1} = \begin{cases} Q \cdot \exp\left(\dfrac{X_{worst}^t - X_{i,j}^t}{i^2}\right) & if\ i > \dfrac{n}{2} \\ X_p^{t+1} + \left|X_{i,j}^t - X_p^{t+1}\right| \cdot A^+ \cdot L & otherwise \end{cases} \tag{3}$$

Where, X_p^{t+1} represents the best position of the discoverer at the time $(\mathrm{t}+1)$, and X_{worst}^t represents the worst position in the t_{th} generation population. A is a $(1 \times d)$ matrix whose elements are all 1 or -1, and it satisfies the following relationship: $A^+ = A^T(AA^T)^{-1}$.

In the iterative optimization process, each generation will randomly select SD individuals from the population for early warning behavior. When the danger is approaching, both the discoverers and the followers will abandon the current food and move to a new position. The position update method is shown in Eq. (4).

$$X_{i,j}^{t+1} = \begin{cases} X_{best}^{t} + \beta \cdot \left| X_{i,j}^{t} - X_{best}^{t} \right| & if\ f_i > f_g \\ X_{i,j}^{t} + K \cdot \left(\dfrac{\left| X_{i,j}^{t} - X_{worst}^{t} \right|}{(f_i - f_\omega) + \varepsilon} \right) & if\ f_i = f_g \end{cases} \tag{4}$$

Here, X_{best}^{t} represents the optimal position in the t_{th} generation population, β is a step size control parameter that satisfies the normal distribution, with a mean value of 0 and a variance of 1. K is a random number of [-1,1] and f_i represents the fitness of the sparrow at the current position. ε is a non-zero minimum value, f_g is the global optimal fitness and f_ω is the global worst fitness.

2.3. The improved sparrow search algorithm

Aiming at the problem in the basic sparrow search algorithm that the discoverers will approach the global optimal solution from the beginning[39], making the search range small and easy to fall into the local optimum, an improved method is proposed: introducing the global optimal solution of the previous generation to update the position of the discoverers. In the method, it is affected by the position of the discoverers of the previous generation and the global optimal solution of the previous generation to avoid falling into the local optimal[40]. Therefore, the equation for updating the position of the discoverers is changed from Eq. (2) to Eq. (5).

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^{t} + \left(f_{j,g}^{t} - X_{i,j}^{t} \right) \cdot \mathrm{W} & if\ R_2 < ST \\ X_{i,j}^{t} + Q & if\ R_2 \geq ST \end{cases} \tag{5}$$

Where, $f_{j,g}^{t}$ is the global optimal solution of the j_{th} dimension in the previous generation and W is a random number of [-1,1]. In addition, the position update method for reconnaissance and early warning is changed from Eq. (4) to Eq. (6).

$$X_{i,j}^{t+1} = \begin{cases} X_{best}^{t} + \beta \cdot \left(X_{i,j}^{t} - X_{best}^{t} \right) & if\ f_i \neq f_g \\ X_{i,j}^{t} + \beta \cdot (X_{worst}^{t} - X_{best}^{t}) & if\ f_i = f_g \end{cases} \tag{6}$$

When $if\ f_i = f_g$, the sparrow will update its position to a random position between the optimal position and the worst position if the sparrow is in the optimal position. When $f_i \neq f_g$, it will update its position to a random position between the worst position and itself.

2.4. ISSA-BP joint algorithm estimation model

The sparrow search algorithm has better global search and local development capabilities. Combining SSA with BP neural network can not only exert the generalization mapping ability of BP neural network, but also improve the shortcomings of BP neural network such as easy to fall into local minimum and slow convergence speed. Figure 2 shows the implementation process of the ISSA-BP joint algorithm.

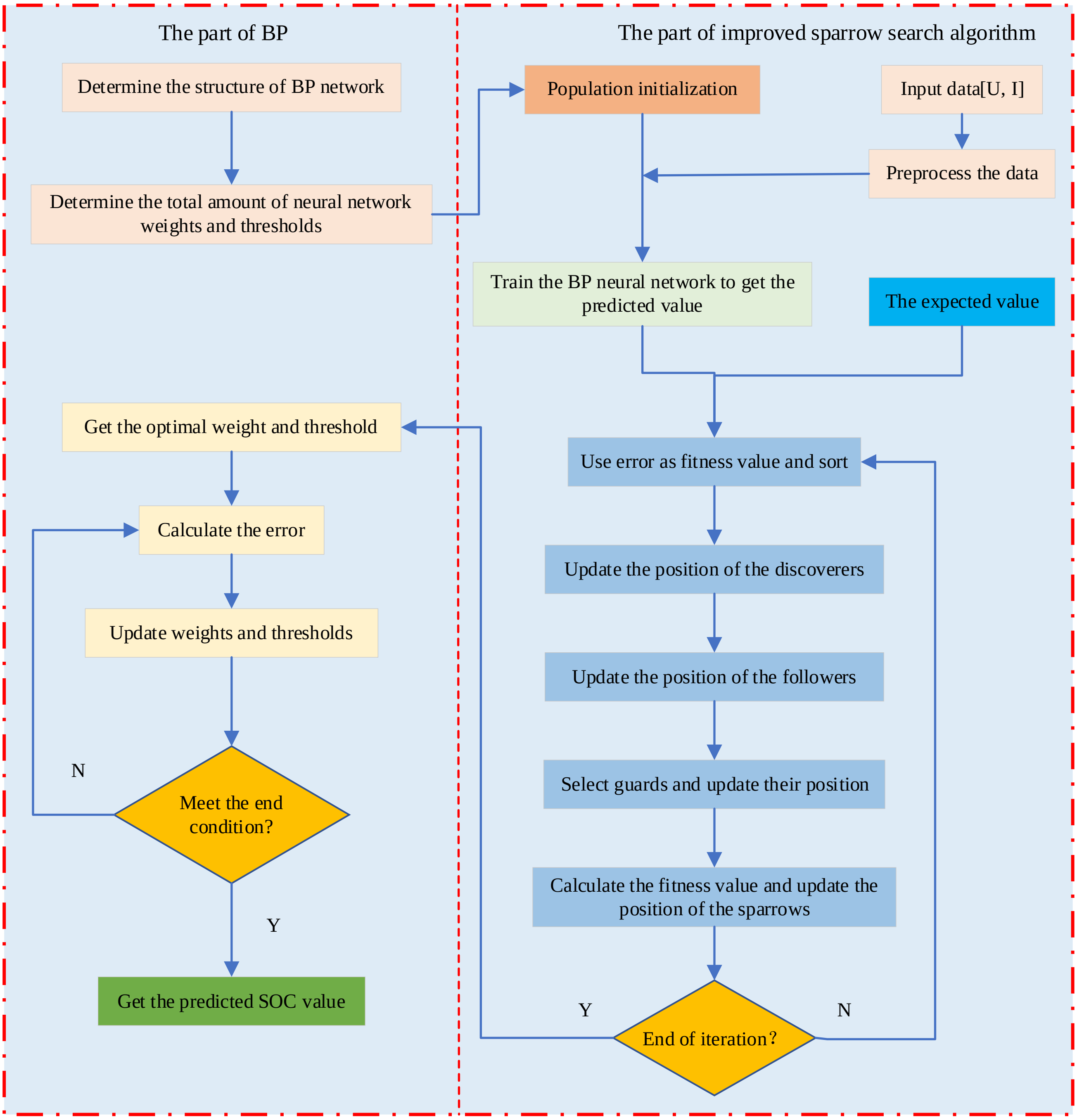


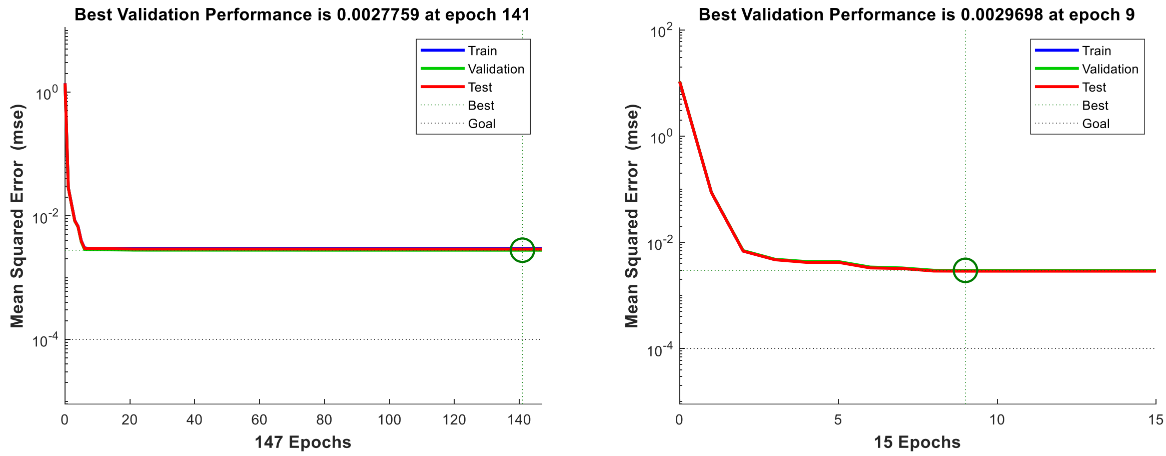
Figure 2. ISSA-BP joint algorithm implementation process diagram

The optimization process can be roughly divided into three parts: ①Determine the BP neural network structure according to functional requirements; ②Use SSA to optimize the weights and thresholds of the BP neural network to obtain the initial optimal weights and thresholds; ③Maintain the structure of the BP neural network unchanged, assign the initial optimal weights and thresholds to the network, and then use the experimental data to test and verify the network.

3. EXPERIMENTAL ANALYSIS

3.1. Data selection

The terminal voltage and discharge current of the lithium-ion battery are selected as the input of the model, and the state of charge of the lithium-ion battery is used as the output of the model. The ISSA-BP model is applied to a lithium-ion battery with a rated voltage of 4.2 V and a rated capacity of 45 Ah, and a state-of-charge estimation model of the lithium-ion battery is established. The model is verified under different working conditions. Set the learning rate of the BP neural network optimized by SSA to 0.1, the training target to 0.0001, and the number of iterations to 1000. The random initial BP neural network is compared with the training error curve of the BP neural network optimized by SSA, and the result is shown in Figure 3.



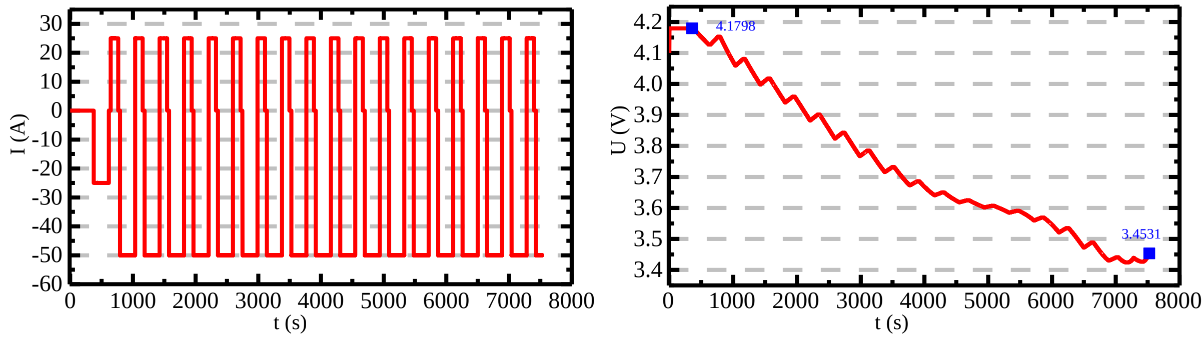
(a) The performance curve of the BP algorithm (b) The performance curve of the SSA-BP algorithm

Figure 3. Performance curves of different algorithms

It can be seen from Fig. 3 that when the number of training times is 9, the error of the SSA-BP neural network is already very small, and the accuracy required by the target has been reached. However, the BP neural network only meets the accuracy requirements when the number of training times is 141. In contrast, the SSA-BP neural network shows a faster convergence rate.

3.2. DST working condition verification

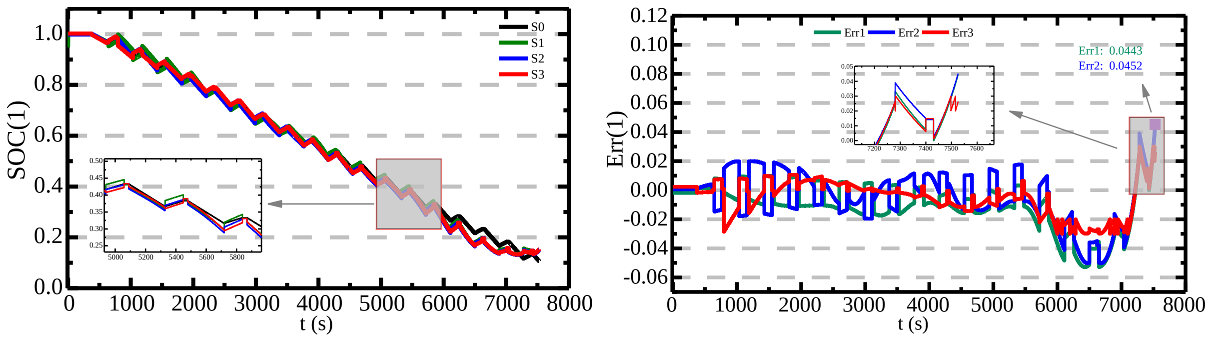
Under DST working condition, the lithium-ion battery is charged and discharged in constant current cycle. The changes of current and voltage are shown in Figure 4.



(a) The variation of current (b) The variation of voltage

Figure 4. Variations of current and voltage under DST working condition

In the figure above, input the current and voltage data under DST working condition into BP, SSA-BP, and ISSA-BP models to obtain the estimation and error results of state of charge change of lithium-ion battery, as shown in Figure 5.



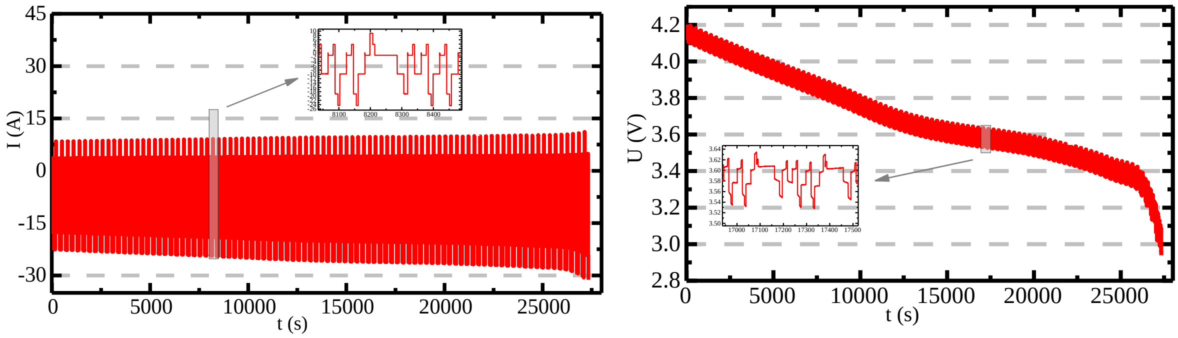
(a) The results of SOC estimation (b) The error of SOC estimation

Figure 5. Lithium-ion battery state estimation results under DST working condition

In Figure. 5(a), S0 represents the reference value of SOC, S1 represents the estimated result of BP, S2 represents the estimated result of SSA-BP, and S3 represents the estimated result of ISSA-BP. In Figure. 5(b), Err1~Err3 are the estimation errors corresponding to S1, S2, and S3 respectively.

3.3. BBDST working condition verification

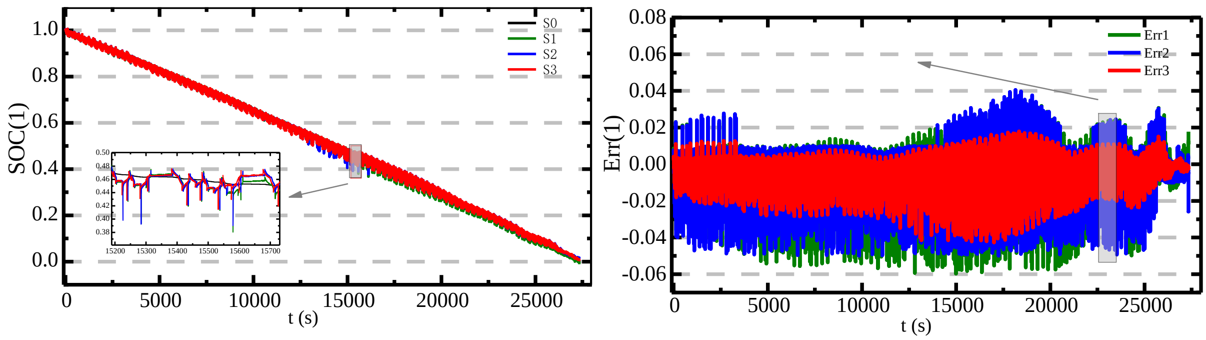
Under BBDST working condition, the lithium-ion battery cycle of constant power charge and discharge is carried out to better measure the power characteristics of the battery. Current and voltage changes are shown in Figure 6.



(a) The variation of current (b) The variation of voltage

Figure 6. Variations of current and voltage under BBDST working condition

In the figure above, the current, voltage are introduced into BP, SSA-BP and ISSA-BP estimation models to obtain the state of charge during the whole experiment. The BBDST condition is more complex than the constant current charging and discharging working condition, the test data under this condition can better reflect the state change of the battery under complex conditions.



(a) The results of SOC estimation (b) The error of SOC estimation

Figure 7. Lithium-ion battery state estimation results under BBDST working condition

In Figure. 7(a), S0 represents the reference value of SOC, S1 represents the estimated result of BP, S2 represents the estimated result of SSA-BP, and S3 represents the estimated result of ISSA-BP. In Figure. 7(b), Err1 represents the estimation error of BP, Err2 represents the estimation error of SSA-BP, and Err3 represents the estimation error of ISSA-BP.

3.4. Results analysis

From the simulation results of DST and BBDST, it can be seen that the output of ISSA-BP is closer to the expected output than BP and SSA-BP, and shows better fitting. Table 1 shows the comparison of SOC estimation results of BP, SSA-BP and ISSA-BP models under DST and BBDST working conditions.

Table 1. Comparison of experimental results of different algorithms under different working condition

Working condition	Algorithm	Average error	Maximum error
DST	BP	1.38%	5.28%
	SSA-BP	1.21%	4.52%
	ISSA-BP	0.98%	2.63%
BBDST	BP	0.78%	5.96%
	SSA-BP	0.61%	5.98%
	ISSA-BP	0.39%	4.26%

In Tab. 1, compared with the BP algorithm, the average error and the maximum error of the estimation results of the SSA-BP algorithm are reduced, which proves that the sparrow search algorithm has an optimizing effect on the BP neural network. In addition, the estimation results of the ISSA-BP algorithm are further reduced on the basis of the SSA-BP algorithm, which proves the feasibility and correctness of the optimization scheme.

The maximum error of the GA-BP model proposed in the literature[41] for SOC estimation is less than 7%. The ISSA-BP model proposed in this paper has a maximum error of less than 5% for SOC estimation. Compared with the improved PSO-BP model with a maximum error of less than 8%[42], the ISSA-BP model proposed in this paper has a maximum error of less than 5%, so the ISSA-BP model proposed in this paper has higher accuracy. Compared with using only BP Compared with the model[43], the maximum error of SOC estimation is 7%, and the error of ISSA-BP model used in this paper is greatly reduced, and the error is less than 5%.

4. CONCLUSIONS

It is difficult and important to accurately estimate the SOC of a lithium-ion battery. The estimation result of the traditional BP algorithm is almost determined by the initial weight and threshold, and it has disadvantages such as being easy to fall into a local minimum. In addition, the traditional sparrow search algorithm also has the defect that it is easy to fall into the local minimum. Therefore, based on the BP network, the improved sparrow search algorithm is used to optimize the initial weights and thresholds globally. The final optimal solution is assigned to the BP network, and the SOC estimation model of the lithium-ion battery of the ISSA-BP neural network is established. According to the simulation experiment results, the estimation result of the ISSA-BP neural network for SOC is closer to the real value than the estimation results of the SSA-BP neural network and BP neural network, and its accuracy is higher. The input data of the lithium-ion battery SOC estimation model established in this paper is only voltage and discharge current, and does not consider factors such as lithium-ion battery temperature and internal resistance. Therefore, the next step of research should be to complete the comprehensive consideration of influencing factors to achieve higher prediction accuracy.

NOMENCLATURE

The symbols used in this research can be described as shown in Tab.2.

Table 2. List of symbols

Symbol	Description
SOC	State of Charge
BP	Back Propagation
SSA	Sparrow search algorithm
ISSA	Improved sparrow search algorithm
DST	Dynamic Stress Test

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