Journal of Computers Vol. 35 No. 3, June 2024, pp. 209-224
doi: 10.53106/199115992024063503015

A Fault Diagnosis Method for Electric Vehicle Charging Circuit Based on Artificial Intelligence Recognition

Ming-Na Xia*

Tangshan Vocational & Technical College,
Tangshan City 063300, Hebei Province, China

tz_na678@126.com

Received 1 May 2024; Revised 1 June 2024; Accepted 19 June 2024

Abstract. In order to reduce carbon emissions and achieve the strategic goal of carbon neutrality, China is vigorously developing the electric vehicle industry, and the manufacturing technology and quantity of electric vehicles have achieved historic breakthroughs. With the explosive growth of the number of electric vehicles in China, the charging frequency of electric vehicles in a certain region is also increasing during the outbreak, leading to a continuous increase in charging faults of electric vehicles. In order to reduce charging faults, this article takes the intelligent diagnosis of electric vehicle charging circuits as the research object. Firstly, the classification of electric vehicle charging faults is established. Based on the fault classification, the charging and discharging process model of electric vehicle power batteries and the fault models of some typical circuits are established. Then, the existing fault data is used as the dataset, and an improved whale algorithm is used to diagnose the collected fault data. Finally, simulation software is used to verify the accuracy and diagnostic speed of the proposed method in the fault diagnosis process. The method in this article meets the design expectations.

Keywords: electric vehicle, fault diagnosis, whale algorithm, intelligent diagnosis

1 Introduction

With the development of China's economic industry in recent years, our country has achieved steady growth in both economic output and personal income, and people's living conditions have greatly improved. With sufficient economic foundation, it is inevitable to pursue a higher quality of life. The proportion of residents' consumption in clothing, food, housing, and transportation in total household expenses continues to increase. Cars have become a necessary consumer goods for contemporary families. Therefore, the demand for cars among modern people is becoming increasingly strong, which in turn stimulates the vigorous development of China's automobile market. However, the increase in car ownership has exacerbated the consumption of fossil fuels such as oil and significantly increased carbon emissions, leading to severe energy and environmental problems. In addition, in terms of China's existing fuel vehicle industry foundation, it is undoubtedly difficult to catch up with advanced foreign technologies, and it is still at a disadvantage in the competition with foreign brands. Based on the above background, the domestic new energy vehicle market is vast, and sales will still maintain high growth [1].

The power source of new energy vehicles is clean energy, which is obtained through charging. Electric energy, as a clean energy source, can alleviate energy crises, reduce carbon emissions, and reduce environmental pollution, which is in line with the goal of building a resource-based society and the "dual carbon" strategy in China. Therefore, new energy vehicles are an important theme for the development of automotive technology and a key development target for governments and enterprises in various countries [2, 3].

With the significant increase in the number of electric vehicles and the frequency of charging, the number of fault cases in the charging process of electric vehicles has also increased. Therefore, ensuring the reliability and safety of the battery pack and charging system during the charging process of electric vehicles will be a huge challenge. During the charging process of electric vehicles, problems such as overcharging and discharging, sensor failures, External Short Circuit (ESC), and Internal Short Circuit (ISC) are common faults in the car charging system [4].

* Corresponding Author

2 Classification and Corresponding Research of Typical Charging Faults

In order to achieve intelligent diagnosis of electric vehicle faults, it is necessary to summarize and analyze the characteristics of existing faults, and provide data support for further intelligent diagnosis methods.

In the actual use of pure electric vehicles, if there is insufficient remaining power of the power battery, it must be charged using charging equipment. Repeated charging can cause a certain degree of loss in the charging system. Secondly, during the charging process, fluctuating voltage and current can also cause damage to the electronic components of the system, leading to charging system failures. Overall, the most common faults currently present are that the vehicle charging interface indicator light does not respond, the relay cannot be engaged, and the dashboard charging indicator light lights up when the vehicle is not charging. As the charging efficiency and system complexity of pure electric vehicles gradually improve, maintenance personnel can use electronic diagnostic technology and diagnostic equipment such as oscilloscopes and decoders to conduct fault checks on the charging system of pure electric vehicles without disassembling the charging system components, and quickly locate the fault point, thereby improving the efficiency of fault diagnosis.

The charging faults of pure electric vehicles mainly involve two aspects: the power battery and charging equipment. By analyzing their charging characteristics, and then analyzing the frequent faults that occur in the power battery and charging equipment during the charging process, we can lay the foundation for proposing fault diagnosis methods during the charging process in the following text.

The core part of electric vehicles is the power battery, and almost all safety issues of electric vehicles are closely related to the power battery. Due to its excellent environmental friendliness and lightweight characteristics, the vast majority of electric vehicle power batteries choose lithium-ion batteries [5].

The charging and discharging characteristics of lithium-ion batteries are shown in Fig. 1.

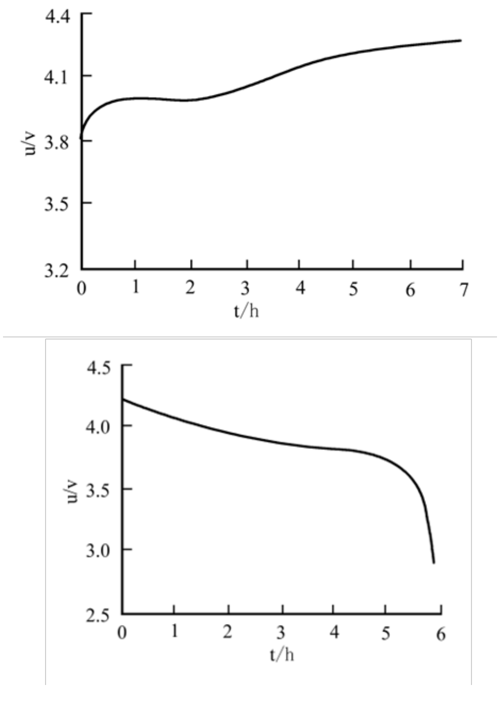

Fig. 1. Charging and discharging characteristics of power batteries

As shown in the above figure, when charging a lithium-ion power battery, the loaded voltage first increases and then tends to stabilize, indicating that when the voltage is stable, it basically reaches a fully charged state. When a lithium-ion power battery is discharged, its voltage follows an S-shaped curve, and the rate of voltage decrease first decreases and then increases [6, 7]. The charging system of electric vehicles includes the power battery itself and the charging management circuit board. Therefore, when analyzing the entire charging system, the system faults on one side of the vehicle mainly focus on vehicle battery faults and vehicle circuit board faults.

Collect maintenance records from various brands and manufacturers, and common power battery failures and their causes are shown in Table 1.

Table 1. Typical battery failure

Fault phenomenon	Cause of malfunction
Reduced battery pack capacity	Early protection of individual batteries
	The battery pack is in the later stage of its lifespan, with a decrease in capacity
	Temperature protection for battery pack
	High energy consumption loads occur in peripheral circuits, such as long-term shallow charging and discharging of air conditioning and car light batteries, resulting in memory effects. The discharge platform is too low to meet the requirements and fails prematurely
	Low discharge environment temperature of battery pack
	Accelerated degradation of battery pack capacity
Charging voltage too high	In the later stage of battery life, internal resistance increases
	Low battery or charging environment temperature
	The battery cell has been overcharged
	The actual capacity of the battery has decreased, and it is still charged at the original relative charging rate, which is higher than the original relative charging rate
	Loose connection between batteries with high internal resistance
	The charge of the battery pack is already very high
	Charger malfunction, high charging current
	The first high current charging of a battery pack after long-term storage
The battery produces an arc and breaks down	Circuit defects and losses of the battery pack itself
	Unreasonable insulation design of power system
Local high temperature	Cooling fan malfunction
	Loose local connectors with high connection resistance
	The internal resistance of the battery in this area significantly increases, resulting in high heat generation
	Design defect, temperature dead angle in the flow field
	External local environmental impact
The battery pack cannot be charged	Increased battery internal resistance

Analyzing the causes of various battery failures helps to quickly locate the fault points during the fault diagnosis process. Among them, the main reason for the decrease in battery capacity is excessive charging and discharging. When the battery is charged normally, its temperature will slowly rise due to its own heat generation. However, due to the relatively timely heat dissipation in this situation, there will be no danger. But when overcharging occurs, its negative electrode will gradually be filled with lithium, so the surface of the negative electrode will be reduced to lithium metal. Lithium ions will undergo a reduction reaction on the surface of the negative electrode material to generate lithium elemental, which reacts with the electrolyte to thicken the SEI film and increase the internal resistance of the battery. Its terminal voltage will also continue to increase during the charging process. When the voltage exceeds a certain threshold, the electrolyte and electrode material will undergo an oxidation reaction, releasing heat and generating corresponding oxygen. The release of these gases further accelerates the rate of electrolyte decomposition, resulting in a large amount of gas being released. The increase in gas will cause a sudden increase in internal pressure. In order to release the gas, the exhaust valve will open, and the corresponding battery will exhaust to the outside. The active substances in the battery cell that are discharged together with the gas, once in contact with the external air, will produce a very violent reaction, releasing a considerable amount of heat. Finally, it caused deformation of the isolation membrane, causing a short circuit between the positive and negative electrodes of the battery, resulting in thermal runaway.

The reason why the battery pack cannot be charged is partly due to a short circuit in individual battery circuits. When the power battery experiences a short circuit, its discharge current will be particularly high, causing an exothermic reaction. This will cause the battery temperature to gradually rise, further causing the shell to melt step by step. In this state, the protective layer of the shell will be ineffective, ultimately leading to electrolyte leakage. When a short circuit occurs in the battery, sparks will be generated, and the leaked electrolyte will be ignited when it encounters the spark, followed by the burning of the plastic shell, ultimately causing the battery to burn. This is because the electrolyte is a flammable liquid.

Battery high temperature. If the battery is exposed to high temperature conditions for a relatively long time, the internal isolation film will decompose due to the high temperature, causing a short circuit in the battery, and then release a lot of heat in a short time, which will lead to other exothermic side reactions. Through experiments, it has been proven that battery explosions, combustion, and other conditions are generally caused by internal short circuits in the battery. Although voltage testing is already performed on batteries when they leave the factory, it is quite difficult to detect internal short circuits as they are mostly formed slowly by the user while using the battery.

The diagnosis of faults in electric vehicle charging systems is mainly divided into the following three categories:

1) A signal processing based solution. It usually analyzes the external voltage and temperature response of the battery pack system to capture abnormal battery pack responses.

2) Model based solutions. Model based methods are easier to quantify and locate specific faults by mining the relationship between faults and model states or parameters. Many scholars have proposed a series of effective methods, but mainly establish models for detecting faults in lithium-ion battery packs through dimensional parameters such as voltage, current, and heat.

3) Based on data-driven solutions. It has excellent performance in general use and is very suitable for application in fault detection of lithium-ion battery packs.

Many scholars have proposed corresponding fault diagnosis schemes for the above-mentioned faults. Reference [8] established an equivalent mathematical model based on the state of charge of the battery, and compared and analyzed the accuracy of the power model and SOC model during the charging process.

Reference [9] takes the EV300 electric vehicle charging system as an example to explore the fault diagnosis methods for electric vehicle charging systems with charging gun insertion induction signal faults and charging conduction signal faults.

Reference [10] defines a comprehensive evaluation index for the impact of large-scale charging station access on distribution system power flow based on the severity of node voltage and branch power flow violations, and proposes a method for determining the optimal electrical access point of charging stations that contributes to the safe operation of the distribution network.

Reference [11] proposes a segmented fuzzy adaptive PID control method to address the issue of insufficient fault resistance of the fuzzy adaptive PID control method for electric vehicle charging systems. Compared with traditional fuzzy adaptive PID control methods, it has better dynamic and static performance and stronger fault resistance.

Zhifu Wang [12] proposed a joint estimation method that integrates multiple methods to estimate the state of batteries. However, it requires the establishment of a complex equivalent circuit model, which is computationally cumbersome and lacks universality, making it impossible to monitor and warn of multiple faults in batteries.

Shuangming Duan [13] proposed that improving the residual network for battery fault diagnosis can achieve an accuracy of 99%, but the data is sourced from the laboratory and may not necessarily achieve good results on actual vehicles.

Wang et al. [14] proposed a dynamic Bayesian hierarchical fault diagnosis model. Although it can achieve certain results for hierarchical faults, it does not diagnose specific faults.

Hui Zhang et al. [15] proposed using long short-term memory neural networks for fault diagnosis of abnormal voltage in power batteries, but did not consider the associated faults and the possibility of overheating and loss of control caused by faults.

Shichun Yang from Beihang University analyzed the reliability of batteries and developed a comprehensive battery control strategy, which reduces the probability of failure and improves the service time before failure. At the same time, he proposed the lithium-ion battery PHM technology, which relies on battery failure, fault analysis and prediction. Focusing on the key technology of PHM, he elaborated on the overall architecture and ideas of PHM technology in the end cloud integrated battery management system, focusing on fault analysis and failure probability prediction, fault based digital twin modeling technology, fault diagnosis and warning algorithms, reliability analysis and testing methods, and reliability growth technology research progress. He summarized the advantages, disadvantages, and shortcomings of existing technologies, and integrated the fault diagnosis of batteries and battery systems with digital twins and cloud computing. Combining is a further improvement in diagnostic technology [16].

Shuangming Duan, after analyzing the fault characteristics during the charging process of electric vehicles, combined with artificial intelligence technology to locate electric vehicle charging faults, proposed a fault localization algorithm based on evidence theory fusion. On the basis of analyzing the hidden dangers in the charging process of electric vehicles, a comprehensive safety protection modeling was carried out, and a structured design was carried out for the safety warning system. A complete electric vehicle charging safety warning process was established to improve its charging safety. The article mentions intelligent diagnosis and positioning methods for faults [17].

The above research results mainly focus on the faults of power batteries and single fault diagnosis, with less involvement in complex and multi-dimensional charging management circuit board faults. Therefore, this article mainly focuses on the diagnosis of arc faults in charging batteries and circuit boards,

The work done is as follows:

1) Clarified the classification of charging faults on one side of the vehicle, namely power battery faults and charging circuit board faults. Firstly, established the charging and discharging model of the power battery, as well as the fault model of the power battery itself. Then, typical bandpass filtering circuits were cut off for arc fault simulation, and a typical circuit fault model was established;

2) Based on the established model, an improved whale algorithm is used to search and diagnose typical faults. At the same time, in order to improve the efficiency of fault diagnosis, the improvement method of the model is explained;

3) Finally, the feasibility of the proposed method was verified through simulation experiments.

The chapter composition of this article is as follows: Chapter 2 is an analysis and summary of relevant research, identifying typical battery faults and some fault diagnosis schemes provided by scholars. Chapter 3 establishes models for power battery and circuit faults, considering experimental environmental conditions. The circuit faults are mainly based on arc fault models. Chapter 4 is a description of fault diagnosis methods, using improved whale algorithms to solve problems, describing the process of improving whale algorithms. Chapter 5 is a simulation experiment to verify the effectiveness of this method for circuit fault diagnosis. Chapter 6 is the conclusion, summarizing the shortcomings of this article and making further research prospects.

3 Establishment of a Fault Model for Charging System Circuits

Battery and circuit board faults are collectively referred to as charging system circuit faults. Monitoring of circuit faults can be analyzed through the charging status and charging demand status of electric vehicles. The battery charging response simulated by the battery model can be compared with the charging status information of the battery. At the same time, the charging status information of the charging machine can be compared in real-time with the charging demand of the battery, so as to timely detect charging circuit faults. In order to use intelligent diagnostic methods to diagnose battery system faults, this section establishes a battery working model and uses the battery charging circuit arc fault model as the main identification model.

3.1 Establishment of Battery Charging Model

Open circuit voltage characteristics and internal resistance characteristics of individual batteries. The relationship between the open circuit voltage U_k of the battery and the state of charge SOC of the battery can be expressed using the following formula:

$$U_k = \lambda_0 - \frac{\lambda_1}{SOC} - \lambda_2 SOC + \lambda_3 \ln\left(SOC\right) + \lambda_4 \ln\left(1 - SOC\right). \tag{1}$$

In the formula, λ_1, λ_2, λ_3, and λ_4 are the fitting coefficients, and the model parameter identification method can obtain the fitting coefficients of this group for different battery types.

The internal resistance characteristics of the battery include polarization resistance caused by concentration polarization and electrochemical polarization, as well as Ohmic resistance characteristics caused by resistance polarization. Two RC parallel circuits connected in series with Ohmic resistance can jointly simulate the internal resistance characteristics of the battery [18]. Therefore, the dynamic circuit model of the battery charging system is shown in Fig. 2.

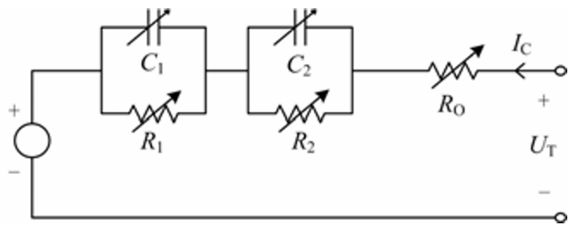

Fig. 2. Battery dynamic model

Obtain charging response information such as voltage or current, SOC, and temperature of the battery through simulation calculations. The expression for the SOC of a battery in the discrete time domain is:

$$SOC_k = SOC_{k-1} + \frac{1}{R}\lambda_{SOC}\lambda_T \eta I_{R(k-1)}\Delta t. \tag{2}$$

In the formula, R is the capacity of the individual battery, η is the reference Coulombic efficiency, λ_{SOC} is the influence coefficient of SOC, and λ_T is the temperature influence coefficient. The formula for calculating the terminal voltage of the battery in constant current mode is as follows.

$$U_{Nk} = U_{k(SOC_k)} + U_{dnk} + U_{dhk} + I_C R_{ok}. \tag{3}$$

U_{Nk} - Battery terminal voltage

U_{dnk} - The concentration polarization voltage of a single battery in the k -th calculation cycle;

U_{dhk} - The electrochemical polarization voltage of the individual battery in the k -th calculation cycle;

$$U_{dnk} = I_{C(k-1)}R_{1(k-1)} + \left(U_{dn(k-1)} - I_{C(k-1)}\right)e^{\frac{\Delta t}{\alpha_1(k-1)}}. \tag{4}$$

$$U_{dhk} = I_{C(k-1)}R_{2(k-1)} + \left(U_{dh(k-1)} - I_{C(k-1)}\right)e^{\frac{\Delta t}{\alpha_1(k-1)}}. \tag{5}$$

$U_{dn(k-1)}$ - The concentration polarization voltage of the single cell battery in the $k-1$ -th calculation cycle;

$U_{dh(k-1)}$ - The electrochemical polarization voltage of the single cell battery in the $k-1$ -th calculation cycle;

I_C - Charging current;

R - Internal resistance of battery polarization;

α - The values at different SOC can be obtained through linear interpolation from the parameter identification template data.

The formula for calculating the charging current during the charging process is as follows:

$$I_{Ck} = \frac{U_{Ck} - \left(U_{dnk} + U_{dhk}\right)}{R_{ok}}. \tag{6}$$

U_{Ck} - Charging voltage;

During the charging process, the amount of heat generated by the charging circuit board caused by the battery's heating also determines the charging speed and is a key factor in measuring whether a fault occurs. The calculation formula for charging current is:

$$T_{k+1} = T_k + K_T \frac{(Q_K - \phi_K)\Delta t}{R}. \tag{7}$$

$$Q_s = -9.4\times10^{-6} Q_1 I_{Ck} + \frac{U_{dnk}}{R_{1k}} + \frac{U_{dhk}}{R_{2k}} + I_{Ck}^2 R_{Ok}. \tag{8}$$

$$\phi_k = \frac{T_k - T_m}{R_k}. \tag{9}$$

Q_s - Generating heat for the battery;

Q_k - Unit electrochemical reaction heat;

ϕ_k - Heat dissipation for the battery;

T_k - Battery temperature;

T_m - Environmental temperature;

R_k - Heat transfer resistance;

3.2 Arc Fault Model of Charging Circuit

According to 3.1, when the charging process malfunctions, it is highly likely to cause charging arcs in the charging circuit, while series circuit arcs can cause breakdown of electronic components such as resistors and capacitors, leading to damage to the circuit board. Therefore, this section establishes a characteristic model of series arc to diagnose typical faults in series circuits. The bandpass filter circuit is a typical circuit that improves the quality of control signals and is widely used in charging circuits [19]. A portion of the bandpass filter circuit in the charging circuit is shown in Fig. 3.

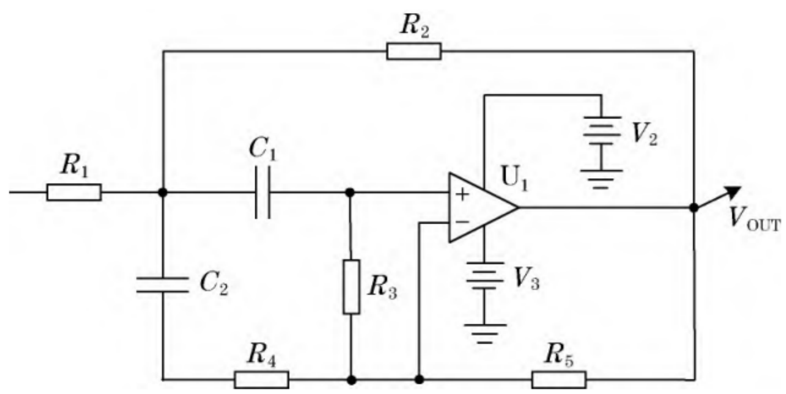

Fig. 3. Bandpass filtering circuit

In order to complete the arc fault simulation experiment of the bandpass filtering circuit, the experimental parameters were set as shown in Table 2.

Table 2. Charging system arc fault experimental platform

Electronic component name	Parameter values
C_1	$20\mu F$
$C_2 \backslash C_3 \backslash C_4$	$42nF$
$C_5 \backslash C_6$	$2nF$
L_1	$12mH$
$L_2 \backslash L_3$	$60\mu H$
$L_4 \backslash L_5$	$50\mu H$
$R_1 \backslash R_2$	1Ω
$R_3 \backslash R_4$	2Ω

Under various working conditions, the location of the arc occurrence is in front of the impedance of the positive bus line (string head), behind the impedance of the positive bus line, before the impedance of the negative bus line, and the impedance of the negative bus line. The principle of discrete Fourier transform is applied for data signal analysis. The signal is discretized in the frequency domain after undergoing discrete Fourier transform, and is converted from the time domain to the frequency domain, thereby achieving the study of spectral characteristics.

Discrete Fourier transform [20] is a widely used signal analysis method that can discretize the DC arc fault current signal in the frequency domain, convert the sampling in the time domain to the sampling in the frequency domain, and thus provide the frequency domain characteristics of the DC arc fault signal. By dividing the entire DC arc fault signal into several small signals of equal length through a time window, sufficient detailed information of the signal can be obtained. This method is computationally simple, technically mature, has a low application threshold, and can effectively distinguish between arc and non arc features. The processing results only contain frequency domain and amplitude information, which requires low information processing capabilities of machine learning models; Although short-time Fourier transform and wavelet transform can also distinguish features with and without arcs, their computation is more complex and their application threshold is higher. The processed results contain three types of information: time domain, frequency domain, and amplitude size, which requires higher information processing ability from machine learning models. Therefore, assuming a signal $x(n)$ is a finite length sequence of length N, its expression is:

$$x(n) = \begin{cases} x(n) & 0 \le n \le N-1 \\ 0 & other. \end{cases} \tag{10}$$

Using discrete Fourier transform to analyze signal $x(n)$, it is found that $x(k)$ is still a finite length sequence of length N. The transformation process can be expressed as:

$$x(k) = DFT\left[x(n)\right] = \sum_{n=0}^{N-1} x(n) e^{\frac{\pi kn}{N}}. \tag{11}$$

In the formula, $x(k)$ is the k -th signal in the signal sequence obtained through discrete Fourier transform. $k \in \left[0, N-1\right]$, then the inverse representation of the signal is:

$$x(n) = IDFT\left[x(k)\right] = \frac{1}{N}\sum_{n=0}^{N-1} x(k) e \frac{\pi kn}{N}. \tag{12}$$

If the original arc fault signal collected by the oscilloscope is directly subjected to Fourier transform, many small current abrupt changes will be lost, resulting in inaccurate spectrum. Therefore, before conducting feature analysis on the fault arc current, it is necessary to determine a reasonable time window to segment the data.

The selection of window size is very important, as a time window that is too large or too small can have a negative impact on data feature analysis. The Fourier transform can be understood as taking the mean of the signal in each frequency band within the window. Therefore, the smaller the window, the better it can reflect small changes in the signal, with good real-time performance and increased computational burden; However, although a large time window may reduce the computational burden, it cannot reflect the real-time nature of the signal well, and the ability to display details is also worse. In order to select the appropriate time window, 2ms, 10ms, and 50ms time windows were used to analyze the fault current signal of the same 8A DC arc. Considering the safety and simplicity of the experiment, this article uses signals collected by transformers for fault arc identification. However, in order to compare the differences in current spectra between arc and non arc states as much as possible, the arc current signals directly collected by current probes are used in feature analysis. The high-frequency component of the DC arc fault signal is generally distributed in the frequency range of 40-100 kHz, and the frequency spectrum range is set to 1-120 kHz. From the analysis, it can be seen that the smaller the window, the clearer the details displayed in the spectrum results, and the more obvious the feature difference between the current spectrum with and without arcs, which is more conducive to network model recognition; However, if the window is too small, it will increase the computational load, which puts higher requirements on the hardware's computing power. Therefore, this article chooses the current spectrum of a 10ms time window as shown in Fig. 4.

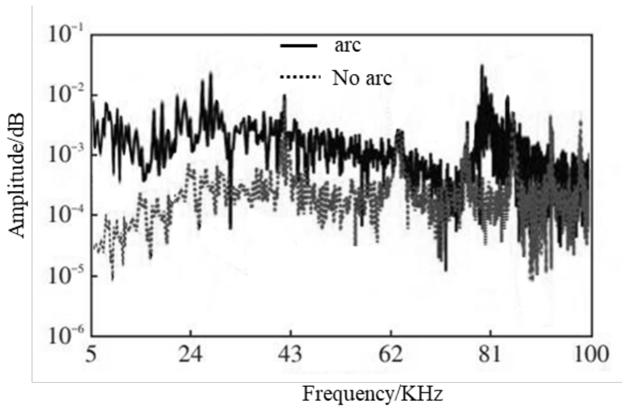

Fig. 4. Current spectrum

After the above analysis, a working model for battery charging was established, and the feature extraction of battery arc faults was completed using Fourier transform. The model is the foundation of intelligent recognition and prepares for subsequent circuit fault diagnosis.

4 Fault Identification of Charging Circuit

Based on the content of the previous chapter, a fault model for the battery itself and a typical electronic circuit fault model were established. In order to improve the diagnostic efficiency of the model, this paper proposes an improved whale algorithm (IWOA) [21] for dimensionality reduction diagnosis of charging system circuit fault data.

Whale Optimization Algorithm achieves optimization goals by simulating processes such as whale encirclement, bubble attack on prey, and random search. Consistent with the principles of classical algorithms such as particle swarm, ant colony, and artificial bee colony, it is essentially a statistical and optimization process. The initial population of the basic whale optimization algorithm is randomly generated, and its distribution is uneven, which can easily lead to low quality of algorithm solutions. In addition, when basic whale optimization algorithms perform search updates in the later stages of iteration, as the search deepens, it may occur that the individual whale being searched stays near the theoretical optimal position, which can easily lead to local optima. Therefore, in order to quickly and accurately identify circuit faults, it is necessary to improve the Whale algorithm and process the arc fault signals in the circuit.

Firstly, the circuit fault signal is subjected to dimensionality reduction processing, and then the dimensionality reduction data is used as input to the algorithm model, and the fault diagnosis result is obtained through algorithm solving. According to the third section, various voltage and current signals will be generated in the circuit during the charging and discharging process. Firstly, standardize the collected fault signals using the following methods:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ x_{31} & x_{32} & \cdots & x_{3m} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{n3} \end{bmatrix}. \quad (13)$$

x_{ij} represents the nth influencing factor of j . Then calculate the correlation coefficient matrix;

$$r_{ij} = \frac{\sum_{k=1}^{n} \overline{x}_{ki} \cdot \overline{x}_{kj}}{n-1}. \quad (14)$$

r_{ij} - The correlation coefficient between the A-th influencing factor and the B-th influencing factor.

Then construct dimensional features and use an improved whale algorithm for fault diagnosis in the reduced data. In the IWOA algorithm, the selection of fitness is crucial. In this paper, the average diagnostic accuracy of fault diagnosis is set to the fitness value of the IWOA algorithm, and the maximum diagnostic accuracy is iteratively searched for. Then, the ELM weight and threshold are fixed at this time. Therefore, the flowchart of the fault diagnosis method for analog circuits is shown in Fig. 5.

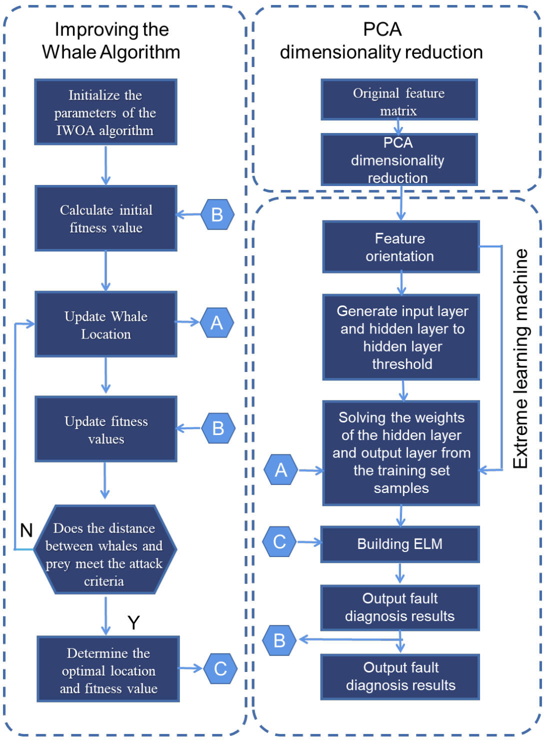

Fig. 5. Schematic diagram of circuit fault diagnosis process

When using the whale improvement algorithm, this paper proposes an adaptive weight strategy scheme to address the problem of local optimal solutions in the algorithm itself. By adaptively changing the weights of variables, the algorithm's adaptability is improved to avoid falling into local optimal solutions. The strategy is represented as follows:

$$\vec{X}^*\left(t+1\right)=\omega\cdot\vec{X}^*\left(t\right)-A\cdot D_1. \tag{15}$$

$$\omega=1-\frac{e^t-1}{e^t}. \tag{16}$$

D_1 - Update the distance between the current individual's position and other individuals in the population;

t - Indicates the number of algorithm iterations;

A - Is a coefficient variable;

$\vec{X}^*(t+1)$ - Indicates a more favorable population location.

The random differential mutation strategy is represented as follows:

$$\vec{X}^*\left(t+1\right)=r\cdot\vec{X}^*\left(t\right)-r\cdot A\cdot D_1. \tag{17}$$

In the formula, r is a random coefficient with a coefficient value between 0 and 1.

The algorithm implementation process is as follows:

1) Initialize the topology of the BP neural network. The formula for the number of hidden layer neurons in BP neural network is as follows: where is the number of input layer neurons;

2) Encode the initial values of the BP neural network to generate the initial population of the whale algorithm;

3) Using the BP neural network method to train the results, calculate the fitness values of all individuals in the whale algorithm, record the whale algorithm individuals with the best fitness value, and select the individuals with the best fitness value for the next generation calculation of the whale algorithm;

4) Select, cross, and mutate individuals with the best fitness values to generate a new whale algorithm population;

5) Repeat steps 2 to 4 until the fitness conditions for fault state recognition of the charging module are met, and obtain the optimal threshold of the BP neural network method;

6) Train a BP neural network method using the determined optimal threshold and output the fault state recognition results of the charging module.

When designing a fault diagnosis and identification model for electric vehicle charging processes, due to the contrast between rule premises and strategy conclusions, sometimes inputting one premise may trigger multiple strategy conditions simultaneously, resulting in many inconsistent output results. Therefore, based on the above intelligent diagnosis model, it is necessary to analyze the applicability of fuzzy rules [20], use two methods of deleting excess and merging similar to optimize the designed fuzzy rules, and ultimately select the most suitable conclusion to complete the diagnosis, thereby improving the accuracy of diagnosis. Therefore, when designing diagnostic strategies, the following two strategies should be integrated into it:

1) Eliminating redundant results, using the fuzzy rule applicability method to find the optimal judgment rule, and removing other strategies that may cause interference. If the maximum applicability of a rule within its input space is a positive number approaching zero, then its impact on the system can be ignored and judged as an redundant strategy.

2) Similarity strategy selection, when there are two or more similar decision strategies, it will cause the system to be unable to eliminate redundant strategies, which will increase the system's computational time. Therefore, when there are similar strategies, if the similarity between the two strategies in their input space is greater than a positive number close to but less than 1, it is considered that these two strategies can be merged.

After the above process, the establishment of fault identification and diagnosis methods has been completed, laying a foundation for the following simulation diagnosis experiments.

5 Acknowledgement

In order to verify the detection effect of the proposed charging fault, this paper conducted tests using a combination of simulation and real experimental environments. Among them, the simulation platform is mainly used to verify the detection effect of the proposed method under ideal conditions, while the experimental platform is mainly used to verify the effectiveness and stability of the proposed method under the setting of simulated arc fault signals. The experimental platform parameters are shown in Table 3. The simulation uses the Urban Dynamometer Driving Schedule (UDDS) as the operating condition

Table 3. Charging system arc fault experimental platform

Electronic component name	Parameter values
CPU	I7-9700K
GPU	RTX4090
Operating system	Win11
Simulation platform	Matlab2023b

In the simulation, a total of 12 lithium batteries are connected in series, and the parameters of the batteries are shown in Table 4. The SOC of the batteries is randomly set, and fault signals are simulated through parallel resistors and ideal circuit breakers. Three experiments are conducted using 12Ω, 6Ω, and 3Ω lithium batteries connected in parallel with sections 2, 7, and 11. The ideal circuit breaker is set to have a short circuit time of 10 seconds and a short circuit start time of 500 seconds.

Table 4. Charging system arc fault experimental platform

Parameter name	Parameter values
Model	PL051747
Nominal capacity	310mAh
Internal resistance	<=120mΩ
Nominal voltage	3.7V
Response time	20s

Then, on the circuit board arc setting, the collected DC arc fault current signal is segmented according to the selected 10ms window and divided into two categories: arc and non arc. Discrete Fourier transform is performed one by one to generate the frequency spectrum of the DC arc fault current signal. The electric vehicle charging system arc fault experimental platform is shown in Fig. 6. The experimental platform mainly consists of the main circuit part and the data acquisition part, which can effectively simulate the series arc fault of the electric vehicle charging system caused by poor contact. The main circuit mainly includes high-power DC power supply, electric vehicle charging station, decoupling network, module line impedance network, connection line impedance between modules and inverters, and fault arc generator. The data collection section mainly includes oscilloscopes, laptops, and current transformers; The locations where the arc occurs are A1, A2, A3, and A4, respectively; To collect high-frequency characteristics of the arc, set the sampling frequency to 300kHz.

During the experiment, a manual switch was used to control the internal short-circuit circuit resistance in parallel with the battery pack unit. When the switch is turned on, the internal short-circuit circuit resistance is connected to simulate the short-circuit electrical effect of the internal short-circuit circuit. When the switch is turned off, the internal short-circuit circuit resistance is cut off.

In order to verify the detection effect of the proposed method, experimental tests were conducted. The Spearman rank correlation coefficient of adjacent cell batteries was calculated and plotted in Fig. 7. The size of the moving window was 23 sample values. In the experiment, the correlation coefficients of adjacent cells were basically close to 1, and each group of results had two open switches for short-circuit simulation.

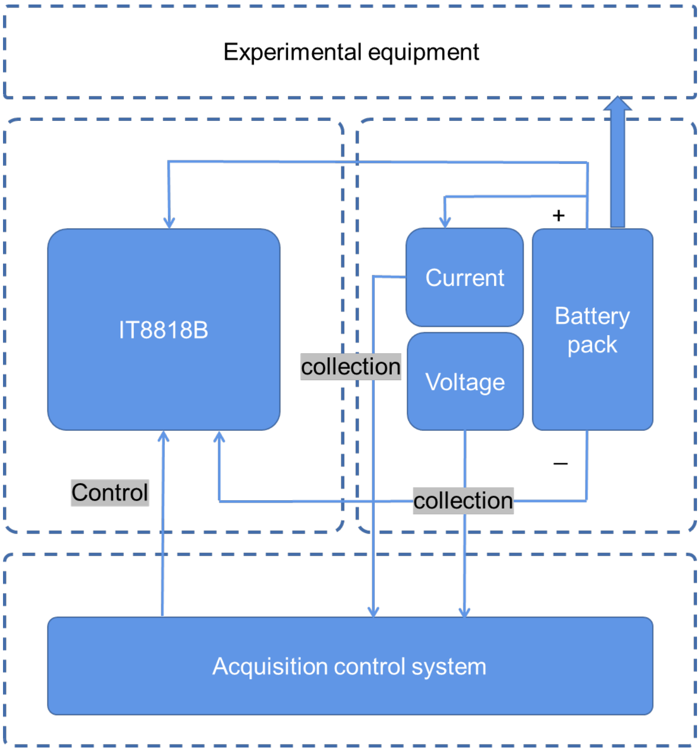

Fig. 6. Schematic diagram of experimental setup

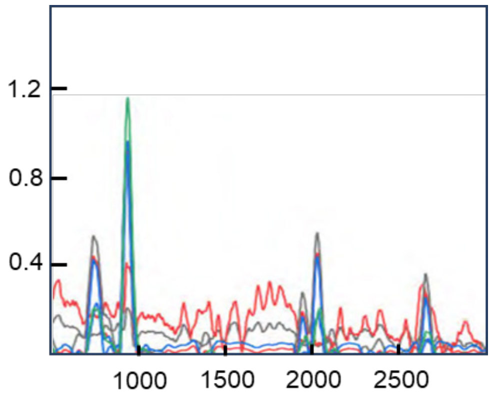

Fig. 7. Test result

To verify the ability of the model to detect fault arcs at different current levels, a test set was used to test the model. The test set includes 200 groups of arc and non arc categories for each current level, with data labels labeled as arc and non arc. Using the test set input to train a series arc detection model for electric vehicle charging systems, experimental verification was conducted, and the verification results are shown in Fig. 8. From Fig. 8, it can be seen that the accuracy of fault detection is not completely the same at different current levels, and the distribution of misjudgments between arc and non arc types is also unbalanced. The main reason is that there are differences in the frequency spectrum distribution of fault arc currents at different current levels; Overall, the accuracy of arc and non arc detection at various current levels has reached over 98%. The results show that the proposed model can effectively detect DC series arc faults at different current levels and has good generalization ability. The predicted results are shown in Fig. 8.

Fig. 8. Arc fault test results

After the above analysis, this section mainly completed the construction of the experimental system, and achieved the expected accuracy in diagnosing battery and arc faults through simulation signals and experimental fault settings.

6 Conclusion

In today's explosive growth of electric vehicles, frequent charging and discharging has led to circuit and battery failures. This article proposes a diagnostic method for common faults to achieve higher diagnostic efficiency. Therefore, for the diagnosis of arc faults in charging batteries and circuit boards, the classification of charging faults on one side of the vehicle, namely power battery faults and charging circuit board faults, was first clarified. Then, a charging and discharging model of the power battery was established, as well as a fault model of the power battery itself. By intercepting typical bandpass filtering circuits and simulating arc faults, a typical circuit fault model was established. Finally, based on the established model, an improved whale algorithm was used to search and diagnose typical faults. At the same time, in order to improve the efficiency of fault diagnosis, the improvement method of the model was explained.

In the research on fault diagnosis of power battery cells and battery packs in this article, it is assumed that there is only one fault cause for the faulty cell, while in reality, there are multiple coupled faults occurring in the battery cell. For the diagnosis of multiple faults, it is necessary to base on multi fault joint diagnosis, find the fault coupling mechanism, diagnose the main causes and secondary factors that cause faults according to the order of fault priority. This article focuses on data-driven fault diagnosis thinking, and does not accurately study the deep mechanism caused by battery faults. There is still insufficient research on the fault heat generation mechanism, thermal runaway, multi fault coupling, and fault degree evaluation. Further research needs to be based on various theories of electricity, heat, and machinery, implement graded and classified fault diagnosis, and establish a fault early warning system to prevent safety accidents from occurring.

At the same time, there are also many shortcomings in this article, which are caused by insufficient research time and technical accumulation. As the research deepens, it will gradually be overcome. The shortcomings are summarized as follows:

1) The classification of battery faults needs to be further deepened. The typical faults in this article are summarized through case studies. With the accumulation of practical fault detection cases, there will be more types of faults.

2) Fault diagnosis focuses on one side of the vehicle, and the entire charging system includes charging stations. Therefore, this article will further study the fault diagnosis methods of charging stations;

3) In terms of fault feature recognition algorithms, the algorithm proposed in this article has further room for improvement in search time and search speed, and is also actively exploring new artificial intelligence algorithms to replace the algorithm proposed in this article.

4) Develop a visual fault identification system to present the identification results more intuitively to maintenance personnel, thereby improving the vehicle's after-sales service experience.

At present, China's new energy electric vehicles are developing rapidly, and the supporting charging facility industry is also accelerating. However, the domestic electric vehicle charging and discharging fault diagnosis and safety operation and maintenance service system is not yet perfect. The actual safety warning effect of electric vehicles and supporting facilities has not reached the expected goals, and the research depth of intelligent diagnosis and safety warning technology for charging and discharging process faults is not enough, resulting in a lack of accuracy in fault positioning and warning level evaluation. In the future, it is necessary to analyze the problem from multiple perspectives and consider more fault phenomena to obtain a more complete fault tree, so as to achieve more and more types of fault diagnosis. More charging data related to electric vehicles and charging equipment can be connected to the electric vehicle charging facility safety operation and maintenance service platform to continuously optimize and verify, Upgrade the system to better serve electric vehicle charging operators.

References

[1] W.-Y. Zhu, Investigation and analysis on the influence of personalized personality on impulsive consumption in automobile marketing, Psychiatria Danubina 34(Suppl. 5)(2022) S282.

[2] H.-L. Zhang, Compared with Traditional Marketing, How Influencer Marketing Affect costumers' Purchasing Behaviors in the Clothing Retailing Industry, Financial Engineering and Risk Management 6(3)(2023) 1-6.

[3] M.-M. Mo, Research on the Development of New Energy Vehicles under the Low-carbon Economy, Auto Time (20)(2023) 130-132+145.

[4] Y.-X. Zhang, B. Li, X.-W. Yan, L. Wang, L.-R. Jiang, X.-H. Diao, T.-Y. Li, Monitoring and early warning method of EV charging failure based on a battery model, Power System Protection and Control 49(10)(2021) 143-154.

[5] S-S. Wang, Y.-J. Chen, S.-Y. Zhang, Z.-P. Mu, Application of Proficiency Testing in the Li-Ion Battery Industry, Environmental Technology 41(12)(2023) 165-168.

[6] S. Pannala, J.A. Turner, S. Allu, W.R. Elwasif, S. Kalnaus, S. Simunovic, A. Kumar, J.J. Billings, H. Wang, J. Nanda, Multiscale modeling and characterization for performance and safety of lithium-ion batteries, Journal of Applied Physics 118(7)(2015) 072017-1- 072017-14.

[7] M. Fleischhammer, T. Waldmann, G. Bisle, B.-I. Hogg, M. WohlfahrtMehrens, Interaction of cyclic ageing at high-rate and low temperatures and safety in lithium-ion batteries, Journal of Power Sources 274(2015)(432-439).

[8] J. X. Xing, Y.-X. Wang, W.-J. Zhang, H.-F. Liu, R. Gu, Y. Shi, G.-R. Xu, An Equivalent Resistance Model of Electric Vehicle Charging Process Based on SOC, Distribution & Utilization 36(8)(2019) 61-66.

[9] J. Zhang, Research on Fault Diagnosis Method Based on EV300 Electric Vehicle Charging System, Automobile Applied Technology (20)(2019) 178-180.

[10] Y.-M. Zhang, Z.-L. Yao, J. Li, Z.-D. Du, Z.-X. Wang, S.-Z. Xu, D. Wu, Z.-H. Huang, Electric vehicle charging station planning strategy based on probabilistic power flow calculation of distribution network, Power System Protection and Control 47(22)(2019) 9-16.

[11] L. Chen, Q. Huang, C.-H. Zhang, J.-S. Tian, Study on control strategy of EV charging system considering fault influence, Power System Protection and Control 40(7)(2012) 117-122.

[12] Z.-F. Wang, W. Luo, Y. Yan, R.-J. Li, Joint SOC-SOH Estimation for Li-Ion Batteries Based on Multi-Method Fusion, Transactions of Beijing Institute of Technology 43(6)(2023) 575-584.

[13] S.-M. Duan, C. Xu, Fault diagnosis of Li-ion battery based on improved residual network, Battery Bimonthly 53(3)(2023) 257-261.

[14] Z.-F. Wang, W. Luo, S. Xu, Y. Yan, L.-M. Huang, J.-K. Wang, W.-M. Hao, Z.-Y. Yang, Electric Vehicle Lithium-Ion Battery Fault Diagnosis Based on Multi-Method Fusion of Big Data, sustainability 15(2)(2023) 1120-1138.

[15] H. Zhang, H.-X. Feng, F. Chen, S.-P. Li, F. Ma, C.-M. Fan, A Diagnosis Method for Abnormal Battery Voltage of Electric Vehicles, Journal of Transport Information and Safety 40(6)(2022) 148-156+172.

[16] S.-C. Yang, X. Wang, F. Chen, Y.-F. Zheng, Y.-L. Zhong, S.-D. Zhou, Advances in prognosis and health management technologies of lithium-ion batteries, Journal of Beijing University of Aeronautics and Astronautics (12)(2023) 1-14.
[17] S.-M. Duan, Z.-B. Chang, Early multiple-fault diagnosis of series battery pack based on charging voltage, Energy Storage Science and Technology 12(10)(2023) 3221-3229.
[18] Z.-L. Fu, J.-M. Zhang, W. Luo, Y. Yan, W.-M. Hao, Joint Fault Diagnosis of SOC and Voltage/ Temperature Abnormalities, Science Technology and Engineering 24(8)(2024) 3260-3268.
[19] G.-X. Pan, L.-W. Pei, X.-Y. Li, X.-T. Wang, Y.-S. Ban, Intelligent Identification Method for Series Arc Fault in Electric Vehicle Charging System, Proceedings of the CSU-EPSA 35(10)(2023) 107-114.
[20] X.-J. Liu, G. Zhou, W.-L. Lu, J.-H. Guo, Application of windowed weighted interpolation discrete Fourier transform in wavelength scanning interferometer, Journal of Huazhong University of Science and Technology (Natural Science Edition) 51(6)(2023) 41-47.
[21] Y.-J. Wu, L.-F. Zhong, J.-W. Li, Q. Ma, D. Yin, H.-F. Zeng, Partial Discharge Diagnosis Method of GIS Based on Whale Algorithm and Improved Wavelet Neural Network, Computing Technology and Automation 42(2)(2023) 25-30.