Leakage and Discharge Fault Detection Technology of Subway Electromechanical Equipment Based on Big Data Analysis

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Abstract. Due to the defects of its own components and the influence of external factors, the metro electromechanical equipment is prone to leakage and discharge faults, threatening the operation safety of the metro. Therefore, the leakage and discharge fault detection technology of metro electromechanical equipment based on big data analysis is proposed. Select appropriate sensors to integrate the operation signals of electromechanical equipment, explore the causes and specific types of leakage and discharge faults of subway electromechanical equipment, and on this basis, apply big data analysis technology, use wavelet transform algorithm to extract the operation signal characteristics and leakage and discharge fault signal characteristics of subway electromechanical equipment, combine support vector machine (SVM) algorithm, select appropriate kernel function, and obtain the optimal classification hyperplane, So as to realize the accurate detection of leakage and discharge faults of electromechanical equipment. The experimental data shows that the maximum success rate of leakage and discharge fault detection using this technology is 95.10%, which fully proves that the leakage and discharge detection performance of this technology is better.

Keywords: Big Data Analytics · Mechanical And Electrical Equipment · The Subway · Leakage Discharge Fault · Feature Extraction · Fault Detection

1 Introduction

The subway is composed of a variety of electromechanical equipment. Electromechanical equipment refers to the general term for electrical and mechanical equipment that includes the mutual conversion of electricity and other energies. Metro electromechanical equipment mainly includes escalators, AFC (automatic fare collection) systems, screen doors, automatic doors, vehicle air conditioners, central air conditioners, ventilation equipment, water supply and drainage equipment, fire sprinkler systems, power control

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systems, etc. [1]. Electromechanical equipment is spread all over the various systems of the subway, and the safe operation of the subway is completed through cooperation. Among all subway installations, electromechanical equipment is one of the key components. The stable operation of electromechanical equipment is of great significance to the safe and economical operation of the subway. Insulation in electromechanical equipment is one of the important conditions to indicate whether it can operate stably. As one of the factors that make the insulation structure of electromechanical equipment age is leakage and discharge faults, it is of great significance and value to complete the accurate monitoring of leakage and discharge faults of electromechanical equipment to improve the economical and reliable operation of subways. Statistical data show that the metro electromechanical equipment is still dominated by insulation failure. The continuation of leakage and discharge faults will not only lead to the burning and damage of the insulation area, but also cause the circuit short circuit between turns and layers. In some metro electromechanical equipment tests, it can be found that rapid detection of leakage and discharge faults of electromechanical equipment can reflect the insulation resistance of electromechanical equipment in advance, and can quickly detect the insulation fault of electromechanical equipment to prevent accidents. Therefore, it is an urgent problem to study the leakage and discharge fault detection technology of metro electromechanical equipment.

At present, researchers in related fields have made research on the leakage and discharge fault detection technology of subway electromechanical equipment. Reference [2] proposes a non-contact detection terminal design scheme based on transient voltage method for the partial leakage and discharge fault of subway underground power supply and distribution equipment. The transient ground voltage method has the advantages of simple and reliable structure, high operating speed and strong anti-interference ability. At the same time, it cooperates with the second-order digital filter to suppress circuit clutter and realizes accurate detection of partial leakage discharge. Reference [3] proposes to start from the measured data at the station site, combined with the power supply mode of each load and the internal power distribution mode of the equipment, analyze the main reasons for the leakage current, and propose corresponding improvement measures, in order to fundamentally solve the leakage current bias of the station power distribution system. It is a major problem to ensure the safe, green and efficient operation of the subway electrical system.

It can be seen that the leakage and discharge fault detection is very important to the safe operation of the subway. Therefore, a research on leakage and discharge fault detection technology of subway electromechanical equipment based on big data analysis is proposed. Firstly, the causes and specific types of leakage and discharge faults of metro electromechanical equipment are analyzed, and appropriate sensors are selected to collect the operation signals of electromechanical equipment. The wavelet transform algorithm is used to extract the operation signal characteristics and leakage and discharge fault signal characteristics of metro electromechanical equipment, and the support vector machine (SVM) algorithm is used to obtain the optimal classification hyperplane to accurately classify the leakage and discharge fault characteristics of metro electromechanical equipment, so as to realize the accurate detection of leakage and discharge faults of electromechanical equipment.

2 Research on Leakage and Discharge Fault Detection Technology of Subway Electromechanical Equipment

The overall model of leakage and discharge fault detection technology for metro electromechanical equipment is shown in Fig. 1.

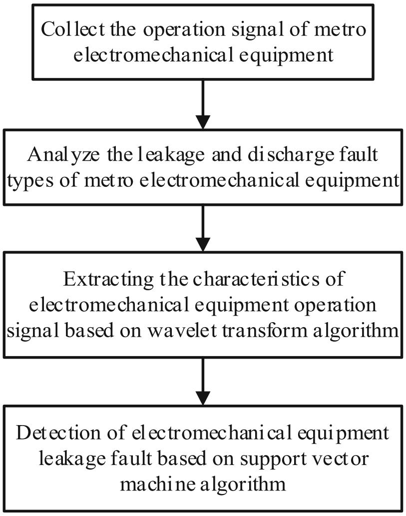

Fig. 1. Overall model diagram of leakage and discharge fault detection technology for metro electromechanical equipment

2.1 Acquisition of Running Signals of Subway Electromechanical Equipment

In order to accurately detect leakage and discharge faults of subway electromechanical equipment, the first step is to use appropriate sensors to obtain complete and accurate operating signals of electromechanical equipment, which will lay a solid foundation for the subsequent screening of operating signal characteristics of subway electromechanical equipment.

In the process of acquiring the operating signal of the subway electromechanical equipment, the performance of the sensor receiving antenna is the key to affecting the integrity of the operating signal transmission. Therefore, the Archimedes helical antenna is used in this study. The Archimedes helix antenna is a planar ultra-wideband antenna made of PCB. The signal attenuation on the helix is not obvious in the effective radiation area, and it does not become significantly smaller outside the effective radiation area, resulting in the terminal truncating the antenna structure., its performance deteriorates, so the Archimedes antenna is not a frequency-invariant antenna. By appropriately changing the termination structure or adding resistance at the termination, the termination effect can be reduced to approximate a frequency-invariant antenna [4]. The polar coordinate formula of the double-armed helix of the Archimedes helix antenna is expressed as:

$$R = R_0 + \alpha(\phi - \phi_0) \tag{1}$$

In formula (1), R represents the distance from any point of the spiral to the polar coordinate center O; R_0 represents the distance from the start point A of the spiral coil to the polar coordinate origin O; α represents the growth rate of the spiral; ϕ Represents the rotation azimuth; ϕ_0 represents the rotation starting azimuth.

The Archimedes helix antenna is a flat-printed structure, and the width of the spiral metal wire is equal to the distance between the wires, forming a self-complementary structure, which enables better impedance matching. In the area outside the effective radiation area, the main electromagnetic radiation has been radiated into the space, and the area outside the main radiation area will not have a major impact on the antenna. Since part of the current still passes through the effective radiation area along the helical coil, reflection will occur according to the principle of terminal effect and affect the performance of the antenna part.

The Archimedes helix antenna designed above is installed on the sensor, and it is effectively connected to provide effective support for the complete acquisition of the operating signal of the subway electromechanical equipment. The obtained operating signals of subway electromechanical equipment are integrated into set $X = \{x_1, x_2, \cdots, x_n\}$, which provides a basis for the screening of subsequent operating signal characteristics.

2.2 Research on Leakage and Discharge Faults of Subway Electromechanical Equipment

Based on the causes of leakage and discharge faults, the types of leakage and discharge faults of electromechanical equipment are divided, as follows:

(1) Suspension leakage discharge fault

In electromechanical devices, the factors that cause levitating leakage discharges are often because air gaps exist in solid insulators or because there are some air bubbles suspended in liquid insulators. The local leakage discharge phenomenon caused by the existence of an air gap in the center of the insulation changes with the change of the gas pressure and the electrodes in the system. The pulse of the partial leakage discharge will occur before the maximum value of the positive and negative half cycles. The amplitude and orientation of such a pulse are roughly the same, and the repeatability is also the same. In addition, the upper and lower amplitudes will be asymmetrical., but this is normal. When the voltage of the equipment rises to a fixed value, the floating leakage discharge of the electromechanical equipment will occur, and its leakage discharge will be larger than the minimum detectable range when it occurs. As the voltage in the follower experiment increases, its leakage discharge capacity is generally constant, but the repetition rate of the leakage discharge pulse will gradually increase. The voltage at the time of extinction is about the same as the voltage that appeared at the beginning. However, the length of time that the voltage is applied has little effect on the leakage and discharge capacity. If there are second or more small bubbles, and leakage discharge occurs, then there will be a higher pulse amplitude when there is a higher voltage.

(2) Corona leakage discharge failure

Corona leakage discharges often occur on high voltage electrical conductors surrounded by gas. In the case of non-uniform electric field, local leakage discharges occur on the surface of the charged conductor in the gas or liquid, where the field strength is high. Corona leakage discharge basically includes two kinds of leakage discharge of metal conductor in liquid insulating medium and leakage discharge in gas. The voltage value of the leakage discharge signal is symmetrical in its positive and negative half cycles. And no matter which half cycle it is in, its leakage discharge duration and interval are the same. In any half cycle, the amplitude of the leakage discharge signal is the same, or distributed regularly. When the leakage discharge position of the electromechanical equipment is very close to the ground, the large pulse of the signal is displayed in the negative half cycle; when the leakage discharge position is close to the high voltage, the displayed pulse appears in the positive half cycle. The initial leakage discharge capacity is greater than the lowest value that can be measured. In the initial period, a large leakage discharge pulse will be generated, and then it will increase with the increase of the voltage. The repetition rate that changes with it also increases. In the case of very high voltage, smaller pulses will be generated in the other half cycle. The small pulse will keep the leakage discharge unchanged as the voltage increases. The extinction voltage coincides with the starting voltage. Because partial leakage discharge will corrode the conductor electrode. Therefore, the amplitude of the leakage discharge signal will change with the change of time.

(3) Leakage discharge failure along the dielectric surface

The occurrence of creepage discharge is due to the existence of dirt and dust on the surface of the insulating medium, which is caused by leakage discharge. Generally, this kind of leakage discharge phenomenon mostly exists on the surface of the outer metal conductor to the medium, but if there are conductive impurity holes of different sizes in the medium, the leakage discharge pattern is almost unchanged. Because of this, it cannot be easily judged whether the waveform is a leakage discharge on the surface of the dielectric. However, if the leakage discharge terminal is a high-voltage electrode and the non-leakage discharge terminal is grounded, the leakage discharge pulse in the positive half cycle will be large and thin, and the negative half cycle will be small and dense; in the symmetrical electrode, this phenomenon does not occur. The phenomenon of leakage discharge is almost the same in the positive and negative half cycles, and the leakage discharge pattern is also almost symmetrical [5].

(4) Internal leakage discharge fault

Some sharp corners and burrs in the metal parts and insulating parts inside the electromechanical equipment are internal leakage discharges. In the electric field, because the dielectric constant of water is much higher than that of electromechanical equipment oil, the impurities are first polarized and attracted to the vicinity of the electrode with the strongest electric field strength, and are gradually arranged along the direction of the electric force line, which produces impurities "small bridge". When the impurities between the two poles are small enough and the distance is large enough, the "small bridge" formed is intermittent. According to the electric field principle, the electric field in the oil will be distorted due to the existence of "small bridges". This is because the dielectric constant of the fiber is relatively large, which strengthens the electric field of the oil at the fiber end, so that leakage discharge occurs from this part, and gas is decomposed. Spark leakage discharge. When the distance between the two poles is small enough and there are enough impurities, the two electrodes may be connected by a "small bridge"; at this time, because the "small bridge" has a large conductance, the current flowing through the "small bridge" will be If it is very large, the "small bridge" will heat up violently, the oil and water near the "small bridge" will gradually boil and vaporize, and finally a gas channel will be generated, that is, the "bubble bridge", which will generate sparks for leakage discharge. If the fiber is not damp, because the "small bridge" has a small conductance, the impact of the spark leakage discharge voltage on the oil will be relatively small; on the contrary, the impact will be relatively large. Therefore, the heating process of the "small bridge" is closely related to the spark leakage discharge of electromechanical equipment caused by impurities.

The above process completes the in-depth exploration of the causes and specific types of leakage and discharge faults of subway electromechanical equipment, and makes sufficient preparations for the subsequent feature extraction of leakage and discharge faults of electromechanical equipment.

2.3 Feature Extraction of Operating Signal of Electromechanical Equipment

Based on the obtained subway electromechanical equipment operating signal set 1, the big data analysis technology-wavelet transform algorithm is applied to scientifically extract the operating signal characteristics of subway electromechanical equipment, which provides a basis for subsequent electromechanical equipment leakage and discharge fault detection.

Singular spectral entropy is one of the many methods for analyzing one-dimensional time series in time domain, and it is a good tool to study noise-containing signals. The basis of singular spectral entropy analysis is the singular value decomposition theorem in matrix analysis. Singular values are commonly used in matrix analysis. Because of their good stability, singular values have important applications in signal processing. Singular value decomposition is an important matrix decomposition method in linear algebra and matrix theory.

The steps to perform singular spectrum analysis on operating signals of subway electromechanical equipment are:

Choose a length of L for the analysis window. L is also known as the embedding dimension in embedded analysis. In order to make full use of the information of the signal, the time delay constant of 1 is selected. Therefore, the pattern data in the signal is intercepted and analyzed with a window order of (L, 1). Construct a pattern data matrix or a trajectory matrix in embedding space. The $X = \{x_1, x_2, \cdots, x_n\}$ sequence is divided into $n - L$ segment pattern data in a pattern window of (L, 1), and these data form a pattern matrix, which is expressed as:

$$Y = \begin{bmatrix} x_1 & x_2 & \cdots & x_L \\ x_2 & x_3 & \cdots & x_{L+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n-L+1} & x_{n-L+2} & \cdots & x_n \end{bmatrix} \tag{2}$$

Perform matrix singular value decomposition on pattern data matrix Y. Assuming that the calculated singular value is $\beta_1 \geq \beta_2 \geq \cdots \geq \beta_L$, then β_i constitutes the singular value spectrum of the operating signal of the electromechanical device. The number of non-zero singular values reflects the number of different patterns included in each column of the data matrix, and the value of the singular value β_i represents the percentage of the corresponding pattern in the total pattern [6]. The eigenvector corresponding to the largest eigenvalue is regarded as the first-order mode, the eigenvector corresponding to the second largest eigenvalue is regarded as the second-order mode, and so on.

Through the corresponding relationship between the singular value and the mode in the mode matrix, we can think that the singular value spectrum $\{\beta_i\}$ is a division of the operating signal of the electromechanical device in the time domain. Therefore, the singular spectral entropy of the operating signal of the subway electromechanical equipment in the time domain can be defined as:

$$\begin{cases} G_s = -\sum_{i=1}^{L} \chi_i \log_2 \chi_i \\ \chi_i = \frac{\beta_i}{\sum_{i=1}^{L} \beta_i} \end{cases} \tag{3}$$

In formula (3), G_s represents the singular spectrum entropy of the operating signal of the subway electromechanical equipment in the time domain; χ_i represents the percentage of the i singular value in the entire singular spectrum, or the i mode in the percentage of the entire pattern.

In the operation process, in order to facilitate the comparison, we generally normalize the singular spectral entropy of the operating signal of the subway electromechanical equipment. After processing, the influence of the selected window length on the operation can be reduced. The expression is:

$$\hat{G}_s = \frac{-\sum_{i=1}^{L} \chi_i \log_2 \chi_i}{\log_2 L} \tag{4}$$

By analyzing the operating signal of subway electromechanical equipment in the frequency domain, its information entropy characteristics, that is, the power spectrum of the operating signal, can also be obtained. Suppose the discrete Fourier transform of running signal $\{x_i\}$ is:

$$x(\delta) = \frac{1}{2\pi n} \sum_{i=1}^{n} x_i e^{-\delta} \tag{5}$$

In formula (5), $x(\delta)$ represents the discrete Fourier transform result of the operating signal; δ represents the discrete Fourier transform factor, which ranges from 0 to 1.

Based on the result of formula (5), the power spectrum of the operating signal of the electromechanical equipment is obtained, and the expression is:

$$H(\delta) = \frac{1}{2\pi n}|x(\delta)|^2 \tag{6}$$

In formula (6), $H(\delta)$ represents the power spectrum of the operating signal of the electromechanical equipment.

The power spectrum $H = \{H_1, H_2, \cdots, H_n\}$ of each frequency can also be regarded as a distinction for equipment operating signals. Then the power spectrum entropy calculation formula is:

$$\begin{cases} F_a = -\sum_{i=1}^{L} \gamma_i \log_2 \gamma_i \\ \gamma_i = \frac{H_i}{\sum_{i=1}^{L} H_i} \end{cases} \tag{7}$$

In formula (7), F_a represents the power spectrum entropy of the operating signal of the subway electromechanical equipment in the frequency domain; γ_i represents the difference measure value of the operating signal.

Obviously, the power spectrum entropy is also the highest value when the signal is white noise, so the operation result of formula (7) can still be normalized, and the expression is:

$$\hat{F}_a = \frac{-\sum_{i=1}^{n} \gamma_i \log_2 \gamma_i}{\log_2 L} \tag{8}$$

The above research obtains the information entropy characteristics of the electromechanical equipment operating signal in the time domain and frequency domain. The two study the operating signal characteristics from different perspectives, which makes the operating signal feature larger and increases the amount of calculation for leakage and discharge fault detection. Therefore, this research applies the big data analysis technology - wavelet transform algorithm to effectively combine the analysis results in the time and frequency domains, and obtain the information entropy characteristics of the time-frequency joint domain [7].

The singular spectral entropy and power spectral entropy of the operating signal of subway electromechanical equipment are mapped into the wavelet space, and the information entropy characteristics of the time-frequency joint domain are obtained by adding weight coefficients. The expression is:

$$K_i = \frac{\tau_1 \hat{G}_s(i) + \tau_2 \hat{F}_a(i)}{5\upsilon_0} \tag{9}$$

In formula (9), K_i represents the information entropy feature of the time-frequency joint domain of the operating signal of subway electromechanical equipment; τ_1 and

τ_2 represent the weight coefficients corresponding to the singular spectrum entropy and power spectrum entropy; υ_0 represents the wavelet transform coefficient.

In the above process, the extraction of information entropy in the time-frequency joint domain, which is the characteristic of the operating signal of subway electromechanical equipment, is completed, which lays a solid foundation for subsequent leakage and discharge fault detection.

2.4 Leakage and Discharge Fault Detection of Electromechanical Equipment

The leakage and discharge fault signals of subway electromechanical equipment are obtained, and the process shown in the previous section is used to extract the information entropy K^* of the joint time-frequency domain. Based on this, combined with the support vector machine algorithm, the accurate detection of leakage and discharge faults of electromechanical equipment is realized.

Support vector machine is a binary classification model. Its purpose is to find a hyperplane to accurately and perfectly segment the sample. The principle of segmentation is to maximize the interval. Before dividing the sample, the data vector in the low-dimensional space is divided. Map to high-dimensional space, establish a maximum interval hyperplane in the high-dimensional space, and completely classify the original data into two independent hyperplanes, that is, realize the binary classification of data [8]. Support vector machines can solve overfitting and local optimal problems very well, and are especially suitable for solving high-dimensional and nonlinear problems.

If a linear function can separate the samples, the data samples are said to be linearly separable. In other words, a linear function in a two-dimensional space is a straight line, a linear function in a three-dimensional space is a plane, and so on. If the dimension of the space is not considered, such linear functions are collectively called a hyperplane. Linearly separable SVMs deal with strictly linearly separable data sets, and all points in the data set must strictly satisfy the linearly separable constraints in order to apply linearly

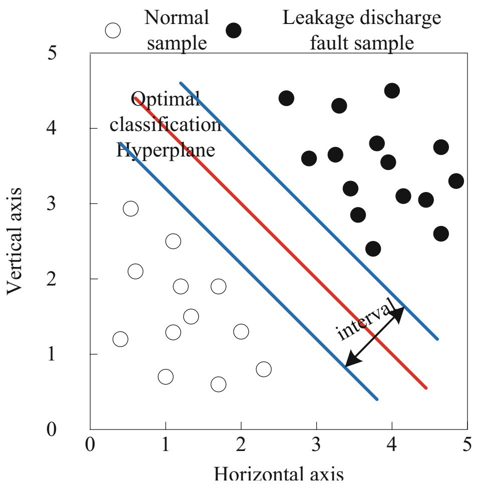

Fig. 2. Example diagram of linearly separable samples

separable SVMs. An example of a linear function in a linearly separable two-dimensional space is shown in Fig. 2.

As shown in Fig. 1, interval calculation is very important in the application of SVM algorithm. The essence of the interval is equal to the projection of the difference between two heterogeneous support vectors on the support vector space. The calculation formula is:

$$\zeta = \frac{(K_i - K^*) \cdot \Omega}{V' \cdot \|\Omega\|} \tag{10}$$

In formula (10), ζ represents the interval; Ω represents the support vector space; V' represents the interval calculation parameter; $\|\Omega\|$ represents the range of the support vector space.

In addition, to construct an SVM with good performance, the choice of kernel function is the key [9]. However, different types of kernel functions correspond to different mapping spaces, thus showing different properties, which in turn determine different nonlinear problem solving capabilities, as well as different applicable scopes and environments. Therefore, it is necessary to select the appropriate kernel function according to the specific data. The four commonly used kernel function types are as follows:

(1) Linear kernel function, which is the most basic kernel function, suitable for dealing with the situation when the number of features is much larger than the number of samples, the expression is:

$$\Psi(K_i \cdot K_j) = K_i \cdot K_j \tag{11}$$

In formula (11), K_i and K_j represent the operating signal characteristics of any two electromechanical devices.

(2) Polynomial kernel function, which is a global kernel function. The higher the data dimension, the easier it is to classify, and the generalization ability is strong, but its learning ability is weak. The expression is:

$$\Psi_d(K_i \cdot K_j) = (K_i \cdot K_j + 1)^d \tag{12}$$

In formula (12), d represents the total number of terms contained in the polynomial.

(3) RBF kernel function, which is suitable for dealing with the situation when the number of features is much smaller than the number of samples. In the absence of prior knowledge of the samples, the RBF kernel function will always achieve good results. Therefore, the RBF kernel support vector machine learning It has strong ability and is the most widely used kernel function at present. The expression is:

$$\Psi_r(K_i \cdot K_j) = \exp\left(\frac{-\|K_i \cdot K_j\|^2}{\sigma^2}\right) \tag{13}$$

In formula (13), σ represents the radial basis variance of the operating signal characteristics of the electromechanical equipment.

(4) The sigmoid kernel function, which is also a global kernel function, has strong generalization ability and weak learning ability. It is relatively limited in application and must meet certain conditions to apply. The expression is:

$$\Psi_g\left(K_i \cdot K_j\right) = \tanh\left(\vartheta\left\langle K_i, K_j\right\rangle + \mu\right) \tag{14}$$

In formula (14), ϑ and μ represent the auxiliary factors of the sigmoid kernel function.

According to the operating signal characteristics of subway electromechanical equipment, the RBF kernel function is selected as the kernel function for leakage and discharge fault detection of electromechanical equipment [10]. By introducing the RBF kernel function into the support vector machine algorithm to obtain the optimal classification hyperplane, the operating signals of subway electromechanical equipment can be quickly and accurately divided into normal signals and leakage discharge fault signals, thus realizing the leakage and discharge fault detection of subway electromechanical equipment. Effective detection.

3 Experiment and Result Analysis

3.1 Experiment Preparation Stage

In order to verify the application performance of the proposed technology, the subway electromechanical equipment room is selected as the experimental object. The selected experimental object subway electromechanical equipment room contains a variety of electromechanical equipment, which can include all types of leakage discharge faults, and meet the technical testing requirements of leakage discharge fault detection.

At the same time, the big data analysis technology - wavelet transform algorithm is applied in the proposed technology, which involves the wavelet transform coefficient υ_0, which directly determines the accuracy of the feature extraction of electromechanical

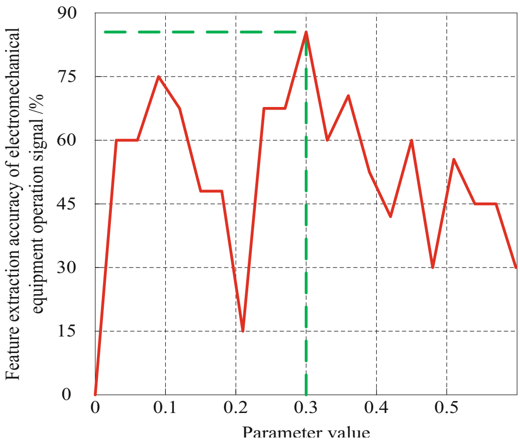

Fig. 3. The relationship between the wavelet transform coefficient υ_0 and the accuracy of feature extraction of electromechanical equipment operating signals

equipment operating signals. Therefore, before the experiment is carried out, the optimal value of the wavelet transform coefficient υ_0 needs to be determined.

The relationship between the wavelet transform coefficient υ_0 obtained through testing and the accuracy of feature extraction of electromechanical equipment operating signals is shown in Fig. 3.

As shown in Fig. 3, when the value of wavelet transform coefficient υ_0 is 0.3, the feature extraction accuracy of electromechanical equipment operating signal reaches the maximum value of 85.5%. Therefore, the optimal value of wavelet transform coefficient υ_0 is determined to be 0.3.

3.2 Analysis of Experimental Results

Based on the selected experimental objects and the determined experimental parameters, the leakage and discharge fault detection experiment of subway electromechanical equipment is carried out. In order to improve the accuracy of the experimental conclusions, the method of Reference [2] and the method of Reference [3] are used as experimental comparison methods, and 10 different experimental conditions are set, as shown in Table 1.

Table 1. Setting table of experimental conditions

Experimental condition number	Electromechanical equipment operating time/d	Leakage discharge fault occurrence times/time
1	30	1
2	60	6
3	90	10
4	120	12
5	150	15
6	180	18
7	210	20
8	240	23
9	270	29
10	300	30

Taking the experimental conditions shown in Table 1 as the background conditions, and the success rate of leakage and discharge fault detection as the evaluation index, the effectiveness and feasibility of the proposed technology are verified. The success rate data of leakage discharge fault detection obtained through experiments are shown in Table 2.

As shown in the data in Table 2, the leakage and discharge fault detection success rates obtained by applying the proposed technology are all greater than the given minimum limit, and the maximum value reaches 95.10%, the minimum value also reached 84.12%, which fully confirms the effectiveness and feasibility of the proposed technology.

Table 2. Leakage discharge fault detection success rate data table

Experimental condition number	Leakage discharge fault detection success rate			Minimum limit
	The method of this paper	Reference [2] method	Reference [3] method	
1	90.12%	85.02%	80.10%	65.00%
2	95.10%	78.23%	79.80%	75.41%
3	89.25%	70.06%	72.77%	61.02%
4	84.12%	64.02%	78.05%	54.12%
5	86.59%	67.95%	76.19%	75.30%
6	88.01%	63.50%	65.92%	61.48%
7	87.52%	64.58%	63.51%	58.49%
8	90.15%	62.85%	50.95%	52.10%
9	91.40%	59.14%	56.80%	48.62%
10	90.06%	60.12%	65.34%	62.78%

4 Conclusion

The subway is composed of a variety of electromechanical equipment. With the upgrading and development of electromechanical equipment, its internal structure has become more and more complex, resulting in a sharp increase in the frequency of leakage and discharge failures, which restricts the development and application of subways. Therefore, a method based on big data analysis is proposed. Leakage and discharge fault detection technology of subway electromechanical equipment. The experimental results show that the technology greatly improves the success rate of leakage and discharge fault detection, provides an effective basis for the handling of leakage and discharge faults of electromechanical equipment, and also provides a guarantee for the safety of subway operation.

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