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The Modified GAN Based-Fault Diagnosis Method of High Voltage Circuit Breaker

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ABSTRACT**:** *In view of the difficulty of obtaining fault data in fault diagnosis research of HV circuit breaker, the generated adversarial network can be used to enhance the fault data of HV circuit breaker. In this paper, an improved generative adversarial network is proposed to solve the limitation of traditional Gans which are difficult to label and classify raw data. First, the original fault data of HV circuit breaker is enhanced by the improved generative adversarial network, and the sample of the training set is expanded. Then, the feature extraction of the expanded training set is carried out, and the fault diagnosis of HV circuit breaker is carried out by convolutional neural network. The experimental results show that the proposed method can improve the fault diagnosis accuracy of HV circuit breaker and ensure the safe operation of HV circuit breaker.*

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I. INTRODUCTION

As a key component of the power system, high-voltage circuit breakers play a pivotal role in the control system and protection mechanism, and their operational stability is the cornerstone to ensure the safe operation of the power grid [1-2]. The relevant survey shows that the mechanical failure of the circuit breaker operating mechanism accounts for 61% of the total failure, and the trend is increasing year by year. Therefore, the implementation of circuit breaker online monitoring and the use of fault diagnosis technology to identify potential defects and faults can not only determine the location of equipment fault and the degree of component fault in time, but also diagnose the root cause of the fault, providing important decision support for the condition maintenance of circuit breakers [3-7].

In order to realize various fault diagnosis of high-voltage circuit breakers, domestic and foreign researchers have proposed many fault diagnosis methods, which can be roughly divided into two categories: The first type is to obtain fault characteristic information of high-voltage circuit breakers through sensors, such as coil current signal, vibration signal, sound signal, etc. [8-10]. Advanced signal analysis and processing technologies such as wavelet packet decomposition, empirical mode decomposition and Hilbert transform are used to extract features from signals [11]. This method is simple and easy to use, but it has some limitations, which makes it difficult to deal with complex situations and fails to realize automatic fault diagnosis. The second type is fault diagnosis method based on deep learning. By combining feature extraction and fault identification process organically, automatic feature extraction is realized, which greatly reduces the need for manual intervention. Methods such as convolutional neural network (CNN), short term memory network (LSTM) and backpropagation neural network (BPNN) are used for fault diagnosis [12-14], but they all need to be based on sufficient training data for the neural network to learn [15]. For the actual working condition of the high voltage circuit breaker, the fault data is difficult to obtain due to the safety consideration and the self-protection mechanism of the high voltage circuit breaker. Considering the impact of small sample data on neural network fault diagnosis [16], this paper considers the use of generative adjunct network (GAN) to enhance the data of limited high-voltage circuit breaker fault signals and expand the existing data sample set.

Recent studies show that using CNN to enrich limited training samples is an effective way to solve the shortage of historical data in fault diagnosis. GAN was first proposed by GoodFellow et al. [17]. Its principle is to fully fit the distribution of real samples through adversarial training, so as to generate high-quality data samples. Compared with the over-sampling method, the data enhancement method based on GAN can effectively increase the diversity of generated samples, so as to better meet the needs of complex industrial scenarios. Therefore, GAN has been gradually applied in the field of fault diagnosis. XUE et al. firstly conduct confrontation training on a small number of fault samples, and then add the generated fault samples to the original small number of fault samples to balance the dataset when the network reaches Nash equilibrium [18]. XIA et al. proposed a small sample fault diagnosis method for mechanical equipment driven by the fusion of twin data and feature enhancement, used the generated adversarial network to enhance the feature of fault data, and used the enhanced data for the training of convolutional neural network model [19]. However, existing Gans have solved the problem of insufficient historical data to a certain extent, but still cannot make full use of unlabeled data.

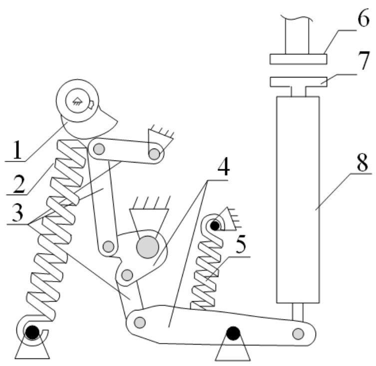
This paper proposes an improved generative adversarial network to classify and enhance the original fault data of high-voltage circuit breakers, use wavelet transform to extract features from the data set, and then use convolutional neural network to diagnose faults of high-voltage circuit breakers. This paper compares the success rate of fault diagnosis before and after using ACGAN as well as the success rate of diagnosis between different models. The superiority of ACGAN-CNN method in fault diagnosis of high voltage circuit breaker is proved.

II. Fault Diagnosis of High Voltage Circuit Breaker

2.1High Voltage Circuit Breaker Typical Mechanical Failure

The mechanical failure of the high-voltage circuit breaker refers to the failure or damage of the mechanical properties during operation, resulting in its inability to operate or run normally. These faults are diverse, complex and often hidden, but they are more harmful and may have a serious impact on the power system.

The high voltage circuit breaker spring operating mechanism is shown in Figure 1. Among them, the fault of the operating mechanism is particularly prominent, which may lead to the operation of circuit breaker rejection, rejection or misoperation, resulting in serious accidents. Common operating mechanism failures include the opening and closing iron core stuck, shaft pin loose, operating lever shift distortion, base screw loosening, energy storage spring off, operating mechanism stuck, etc. [20-21].



1: CAM，2: Closing Spring，3: Connecting Rod，4: Bent Arm,5: Opening and Closing Spring

6: Stationary Contact，7: Movable Contact，8: Insulating Tie Rod

Figure 1: Schematic diagram of high voltage circuit breaker spring operating mechanism

(1) Core jam: core jam failure usually comes from the uneven gap between the core and the coil or the accumulation of deposits on the surface of the core. In addition, the uneven surface of the iron core can also cause this failure. The core sticking will aggravate the erosion and damage of the insulation material by the arc, affect the insulation performance of the circuit breaker, reduce its carrying capacity, and then lead to the increase of the fault frequency of the high-voltage circuit breaker.

(2) Shaft pin loose: The high voltage circuit breaker is usually connected to the equipment by bolts or nuts and other fixed parts. With prolonged vibration or use, these connectors may gradually loosen or become damaged, resulting in the breaker's shaft pin loosening. In addition, if the circuit breaker is overloaded for a long time, it will make the shaft pin and other components bear additional pressure, increasing the risk of loosening or damage, resulting in high voltage circuit breaker failure.

(3) The distortion and deformation of the operating rod switch: in the repeated opening and closing operation process of the external high-voltage circuit breaker, the contact separation stage will exert continuous impact on the switch attached to the control rod, gradually causing the distortion and shape change of these components. The high frequency of this operation may cause long-term damage to the surface layer of the paddle, resulting in impairment of its original flat characteristics, which in turn has the risk of triggering abnormal functioning of the HV circuit breaker.

(4) Loosening of the base: the phenomenon is mostly caused by improper tightening or relaxation of the base bolt. In particular, insufficient bolting will reduce the contact range between the base and related equipment and weaken its support efficiency; On the contrary, once the bolt is loose, it will cause the stability of the base to decline, resulting in the position deviation of the circuit breaker, which may have adverse consequences such as non-cohesive conductive contact and prolonged arc duration. In addition, the unfirmness

of the base may also promote the vibration of the internal components, accelerate the aging speed of the equipment, increase the probability of failure, and interfere with the normal operation of the circuit breaker from the side.

(5) Mechanism card: Long-term operation in a complex external environment will expose the circuit breaker operating mechanism to dust and impurities in the air, which will accumulate on the surface of the mechanism. At the same time, the components of the mechanism gradually age over time, increasing the friction, which in turn affects its normal operation. The mechanism sticking will not only lead to unstable operation, but also have a negative impact on the performance of the circuit breaker, and aggravate the friction and wear between parts, ultimately leading to the decline of reliability and service life [23].

(6) Energy storage spring fall off: energy storage spring is composed of spring, tie rod, hook and other accessories, is an important part of high voltage circuit breaker. These springs are compressed when the circuit breaker is turned off, and a certain amount of energy is stored. The control mechanism releases these springs when the switch needs to be turned off, restoring them to their original state. This process converts the stored energy into mechanical energy by pushing the tie rod in motion, which causes the circuit breaker to close, thus converting it into motion energy. This mechanism ensures that the high-voltage circuit breaker, which ensures the safe and reliable operation of the power system, can be opened and closed quickly and reliably when needed. If the energy storage spring falls down, it will greatly increase the probability of failure of the high-voltage circuit breaker.

2.2Feasibility Analysis of Fault Diagnosis Based on Vibration Signal

In the fault diagnosis of high voltage circuit breaker, the non-invasive fault detection method based on vibration signal has been widely used. In this method, vibration sensors are used to obtain real-time vibration signals of high-voltage circuit breakers during operation, and key fault information is extracted from these signals through feature extraction. According to different fault locations, the diagnosis process can effectively determine the time and type of the fault, and then analyze the running status of the device. Because of its high accuracy and reliability, vibration signal feature extraction method has been widely recognized by professionals in the industry, and has become the main way to evaluate the health status of high-voltage circuit breakers. In this way, potential problems can be detected early, the risk of equipment failure can be reduced, and the safety and stability of the system can be improved [22].

Mechanical vibration signal is an indirect measurement method, which can be monitored near the grounding pole of the circuit breaker, and can effectively avoid the safety risk in the monitoring process. In addition, extracting the characteristic signal of mechanical vibration not only does not damage the internal structure of the high-voltage circuit breaker, but also obtains a lot of time domain and frequency domain information about the high-voltage circuit breaker. Among them, the time domain features include vibration time domain waveform, peak value and RMS value and envelope analysis. Through the above features, the operating time, acceleration process and smooth operation of the circuit breaker can be identified. The characteristics of frequency domain include spectrum analysis, frequency component and frequency band energy distribution. The time domain characteristics are mainly analyzed by using short-time Fourier transform and wavelet transform, which is suitable for capturing the burst and discontinuous signal changes during the operation of circuit breakers. The above features extracted from vibration signals are analyzed, and then nonlinear learning methods are used for fault prediction, state detection and fault detection [23-25].

III. The Modified GAN Based-Fault Diagnosis Methods

3.1 GAN

Generative adversarial network is a new generative model based on machine learning. From the perspective of structure, it is composed of generator D and discriminator G based on deep neural network. In the first step, the generator is responsible for capturing the distribution pattern of fault sample data, and identifying the signal characteristics and distribution characteristics of normal samples and fault samples. The second step is to input the fault sample into the discriminator to identify the probability that the sample contains the true value. After several alternate training, the abnormal sample can be completely identified, and Nash equilibrium can be reached to generate the basic structure of the adversarial network model, as shown in Figure 2.

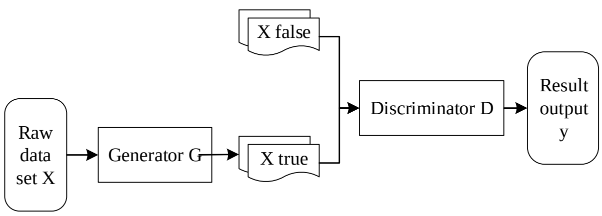


Figure 2: The infrastructure of GAN

The overall data probability p(x) in the original data set is uniformly distributed, and the original data set of input generator D is converted into a random vector, consistent with the real data sample probability distribution. The optimization goal of generating adversarial network is to make the probability distribution of output data of the discriminator consistent with the real fault data sample. The sample space of the output result is compressed to [0,1]. When the vector of the rotational discriminator takes the true value, the output probability approaches 1. When the vector of the input discriminator takes the false value, the objective function ζ(G,D) of the generated adversarial network can be expressed as:

$$min\ max\xi(G,D) = e_{pd(x)}(lnp_d(x)) + e_{pg(x)}(ln(1-p_g(x))) \quad (1)$$

where: $e_{pd(x)}$ is the model expectation function; $e_{pg(x)}$ is the actual function of the model; $p_d(x)$ and $p_g(x)$ are the probability functions of the output of the original fault model generator and discriminator, respectively. Only when the condition of $p_d(x) = p_g(x)$ is satisfied, the optimal solution in the global scope can be obtained.

3.2 ACGAN

Traditional GAN is a game data generation algorithm based on Nash equilibrium theory. This max-min optimization process means that when the game between the generator and the discriminator reaches Nash equilibrium, the generator can learn the laws that conform to the real data distribution. However, the traditional Gans have the problem that the network is not convergent and the unstable mode is easy to collapse. To solve this problem, conditional generative Adversarial network (CGAN), semi-supervised generative Adversarial network (SGAN) and information generative Adversarial network (infoGAN) have been solved to some extent, but all have their own limitations.

CGAN adds additional information y to the generator and discriminator, such as class labels or data attributes, which makes the GAN model expand into a conditional model. However, the limitation of CGAN is that it cannot achieve the effect of completely unsupervised learning, and all data categories must be entered manually.

The output of the generator in SGAN is divided into two parts, namely the classification vector and the pseudo-option. If the number of classes is N, the length of the output vector is N+1, and the input of the judge is the real data and the generated data without class information. While this output gives SGans the ability to identify data, the generator does not generate data by category.

InfoGAN uses mutual information theory to try to prevent mutual information c from being lost in generators. Compared with the original GAN, it has one more input $\lambda I(c;G(z,c))$, which represents the mutual information between c and the output of the generator. The greater the value, the greater the correlation between c and the output of the generator. But the limitation of infoGAN is that latent variables are not categories that the experimenter can control.

In view of the shortcomings of CGAN, SGAN and infoGAN, ACGAN is improved respectively. It combines the advantages of CGAN, SGAN and infoGAN, and enables the generator to make maximum use of the information of noise Z and label C at the same time by giving the judge the ability to judge the truth degree and classification of data. The loss function of ACGAN has two parts, as shown in equation (2) and equation (3) :

$$L_{\mathrm{S}} = E[\log P(S=\mathrm{real} \mid X_{\mathrm{real}})] + E[\log P(S=\mathrm{fake} \mid X_{\mathrm{fake}})] \quad (2)$$

$$L_{\mathrm{C}} = E[\log P(C=c \mid X_{\mathrm{real}})] + E[\log P(C=c \mid X_{\mathrm{fake}})] \quad (3)$$

where :S is the true or false label of the sample; X_{real} is the real sample, X_{fake} is the generated sample; P is the probability; L_{S} is the probability that the recorded data is true; L_{C} is the probability that the recorded data is classified correctly.

The requirement for the judge D is to maximize the sum of L_{S} and L_{C}, and the generator G is to maximize the difference between L_{C} and L_{S}. When the two reach Nash equilibrium, the output data can be considered credible.

3.3 Fault Signal and Data Enhancement

The actual high-voltage SF6 circuit breaker is used as the experimental platform, and the model DH131E single-axis acceleration sensor is used to record the vibration signal of the circuit breaker. The frequency response is 1-8000Hz, and the measurement range is 0-500m/s2. When the closing instruction is received, the data acquisition system starts to record data, the sampling frequency is 10khz, and the sampling period is 300ms. This paper focuses on collecting three diagnostic signals of high voltage circuit breakers: normal, iron core jammed (fault 1) and loose base (fault 2).

According to the process shown in Figure3, ACGAN model was used to enhance the original vibration signals of the high voltage circuit breaker operating state. The vibration signals of the three operating states were obtained as shown in Figure 7, 8 and 9, so as to achieve the purpose of expanding the original sample set.

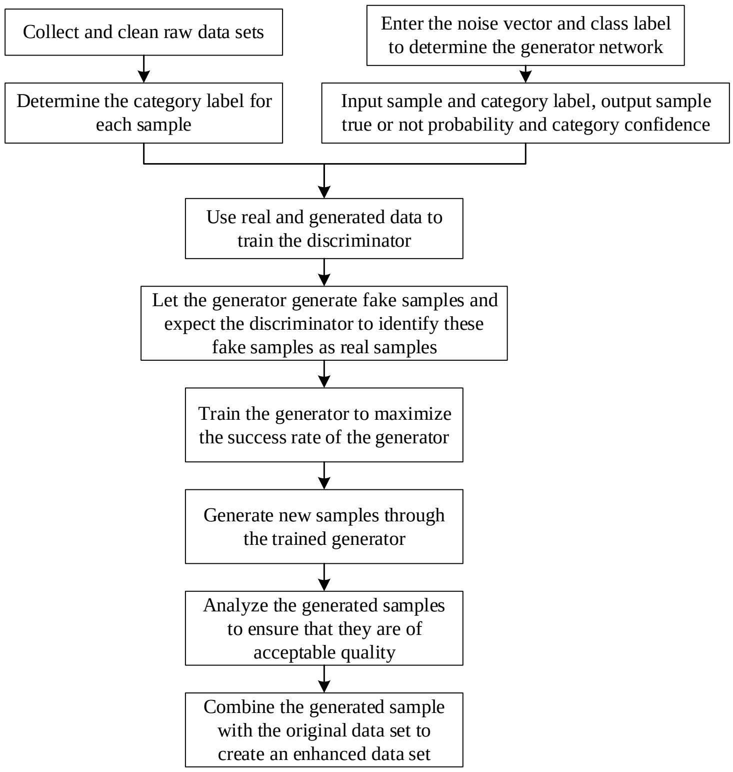


Figure 3:ACGAN data enhancement process

3.4 Wavelet change feature extraction

Wavelet transform is called signal analysis microscope, it can display low frequency information globally on a large scale, and can display high frequency characteristics locally in a small range. Although many methods such as Wigner-Vile (WV) distribution, short-time Fourier transform and wavelet transform can be used to convert the original signal into time-frequency image, some of them have some limitations. The window size of the short-time Fourier transform is fixed. The WV distribution will be disturbed by cross terms, and in the time domain, the general wavelet transform can be expressed as:

$$W_{\varphi}(a,b)=\frac{1}{\sqrt{a}}\int x(t)\varphi^{*}\left(\frac{t-b}{a}\right)\mathrm{d}t, a>0 \quad (4)$$

In this paper, wavelet change is used to extract the feature of the vibration signal samples of the original and enhanced data sets, which is convenient for the fault diagnosis of high-voltage circuit breakers by convolutional neural network.

IV. The ACGAN Based-Fault Diagnosis Methods of High Voltage Circuit Breaker

4.1 Model structure and parameter analysis

In this paper, 80 original data samples of high voltage circuit breaker faults and 120 sets of enhanced data generated by ACGAN were selected. Among them, 60 sets of original data samples were selected as the training set, the remaining 20 sets were selected as the test set, 100 sets of enhanced data were selected as the training set, and the remaining 20 sets were selected as the test set. Therefore, the 200 data samples were divided into 160 training sets and 40 test sets. In the convolutional neural network design adopted in this paper, the format of each group of input samples is 64×24 size matrix, the training set dimension is 64×24×160, and the test set dimension is 64×24×40. In the neural network structure, ReLU function is selected as the activation function. In order to reduce the dimension of data and extract features, in terms of convolutional layers, the number of convolutional layers and pooled layers is 2, the first layer has 32 convolutional nuclei, the size of convolutional nuclei is 3×3, and the second layer has 64 convolutional nuclei, the size of convolutional nuclei is 3×3, and the step size A is 1. The pooling layer applies maximum pooling. The window size F of the pooling layer is fixed as 2×2, the number of the first layer is 32, the number of the second layer is 64, and the step length

A is 2. The fully connected layer has 128 neurons and is 1×1 in size. The initial learning rate is set to 0.5, the minimum learning rate to 0.01, the maximum number of iterations N to 100, and the reference convergence accuracy to 0.1. Parameters and label Settings are shown in Table 1 and Table 2.

Table.1Convolutional neural network structure parameters

Network layer	Nuclear size	Step size	Number of nuclei
Convolution layer 1	3×3	1	32
Pooled horizon 1	2×2	2	32
Convolution layer 2	3×3	1	64
Pooled horizon 2	2×2	2	64
Fully connected layer	1×1		128

Table.2Label setting

State type	Tag
Normal condition	1
Core stuck	2
Loose base	3

4.2Result Analysis

Experiment 1: CNN was used for fault diagnosis of high-voltage circuit breakers. The success rate of fault diagnosis is compared between the original small sample data set and the fusion data set enhanced by ACGAN, as shown in the figures below.

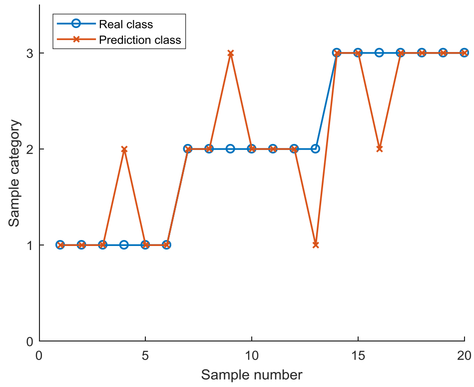


Figure 4:20 original samples in CNN

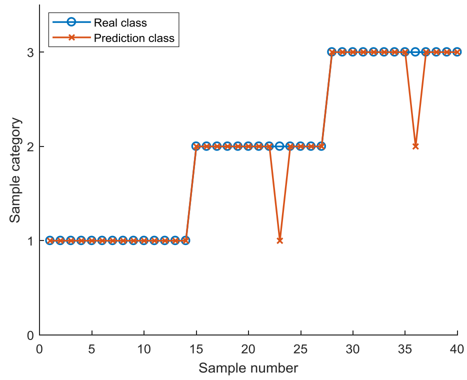


Figure 5: 40 samples in ACGAN-CNN

It can be seen that the diagnosis success rate of the original small sample without data enhancement is 80%, while the diagnosis success rate of the fusion sample set enhanced by ACGAN data is increased to 95%, and the accuracy rate is also greatly improved under the condition of higher sample size, which fully demonstrates the superiority of ACGAN in the fault diagnosis process of high-voltage circuit breakers.

Experiment 2: In order to prove the superiority of the diagnostic scheme combined with ACGAN and CNN, the diagnostic scheme of LSTM and ACGAN-LSTM was set for the same sample as a comparison, and the results were shown in the figure below.

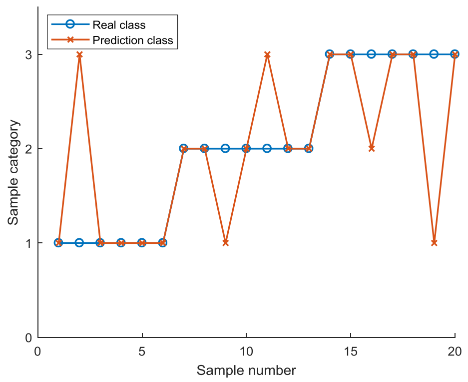


Figure 6:20 original samples in LSTM

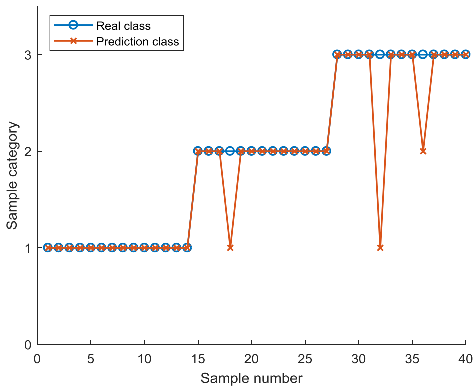


Figure 7: 40 samples in ACGAN-LSTM

It can be seen that the diagnostic success rate of LSTM for 20 groups of original small samples is 75%, slightly lower than that of CNN, while the diagnostic success rate of fusion sample set enhanced by ACGAN data is increased to 92.5%, 17.5% higher than that of original small samples, but slightly lower than that of ACGAN-CNN. The superiority of ACGAN-CNN scheme in fault diagnosis of high voltage circuit breaker is proved.

V. CONCLUSION

Aiming at the difficulty of obtaining fault data in HV circuit breaker fault diagnosis research, this paper proposes a HV circuit breaker fault diagnosis method based on improved generative adversal network. In order to solve the limitation that traditional GAN is difficult to label and classify raw data, this paper proposes an improved generative adversal network. Through the improved generative adversarial network, the original fault data of HV circuit breaker is enhanced, the training set sample is expanded, and the fault diagnosis of HV circuit breaker is carried out by convolutional neural network. The experimental results show that the proposed method can improve the fault diagnosis accuracy of high voltage circuit breaker, and the combined diagnosis scheme of ACGAN and CNN is superior. This paper provides a new technical scheme for mechanical fault diagnosis of high voltage circuit breaker, and provides guidance for fault diagnosis of high voltage circuit breaker, which has important application value and practical significance.

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