Research on UHF PD detection method based on improved DBN

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Abstract. With the development of power grid technology and the widespread application of gas insulator switchgear (GIS) equipment, the power supply reliability of the power system has been greatly improved, but the problem of partial discharge (PD) faults in GIS has always been prominent, seriously affecting the safe and stable operation of the power grid. How to quickly determine the type and cause of GIS discharge is the key to online PD detection. In this paper, in order to deal with the very complicated data processing of ultra-high frequency (UHF) PD, the time-consuming and low efficiency of manually judging the type of PD, a classification model of UHF PD system based on deep confidence network (DBN) is established and an automatic classification method for UHF PD based on improved DBN is proposed; the activation function Sigmoid is improved to effectively prevent the occurrence of the gradient disappearance problem; the optimized DBN parameters are used to train and classify data of different PD types. The classification accuracy rate of the test results reached 96.7%, realizing the rapid classification evaluation of UHF PD types.

1. Introduction
GIS has significant advantages such as good insulation, high reliability, high safety, and small footprint, so it is widely used in power systems [1]. Since GIS is a fully enclosed combined electrical appliance, internal faults are not easy to be discovered and dealt with in time. The vast majority of GIS equipment failures are due to internal insulation aging, PDs continue to occur, and eventually lead to a series of serious consequences such as GIS equipment damage. Therefore, online inspection of GIS equipment, early detection and resolution of internal insulation problems and failures has far-reaching consequences significance. When a PD occurs in power equipment, it usually generates current pulses, electromagnetic radiation, ultrasonic waves, optical radiation, and decomposition to produce new substances, and will cause local overheating. Therefore, according to the different physical and
chemical processes caused by PD, the detection methods include pulse current method, radio frequency method, UHF method, ultrasonic detection method, chemical detection method, infrared thermal imaging method, and optical detection method that has emerged in recent years [2]. The pulse current method is to detect the pulse current generated by the PD through the coupling capacitor, thereby judging the intensity of the PD; the radio frequency detection method uses the radio frequency sensor to detect the PD, and stimulates the electromagnetic signal in the 1-30MHz frequency band, and passes through the follow-up circuit Treat to get the amount of PD. These two methods can quantitatively detect PD, but they have poor immunity to electromagnetic interference and are not suitable for online rapid monitoring. The chemical detection method judges the situation of the PD by detecting the composition and content of the decomposition products produced by the PD of the insulating material. The infrared thermal imaging method and the optical detection method are still in the experimental research stage, and there are few application examples. The UHF detection method is to use the high frequency signal of 300-3000MHz to detect PD. This method has the advantages of strong anti-electromagnetic interference ability and can locate the local discharge source [3].

Literature [4] analyzed the PD characteristics and frequency spectrum of various transformer defects, and found that adjusting the reflection loss of the sensor by forming a resonance point at a specific frequency can improve the sensitivity of the UHF sensor optimized by the transformer. A local discharge power source location algorithm based on PD pulse radiated electromagnetic waves is proposed in Literature [5]. This algorithm is more accurate than the existing method because it takes into account the effects of reflection, refraction and diffraction generated by the UHF signal in the equipment slot. Literature [6] developed a unique time series decomposition and long short-term memory the pattern recognition method of the network realizes the detection of phase-to-ground faults and the frequent occurrence of branch impact on conductors on such conductors. The experimental results prove that the classification results have greater superiority and practicability. Literature [7] proposed a PD denoising method based on wavelet transform to improve the accuracy of PD detection. Literature [8] applied support vector machine to pattern recognition of typical defects of gas-insulated switchgear including free particles, metal spikes, floating metal, and insulator defects, which proved to have good robustness and generalization ability.

The above researches based on the UHF detection method have obtained good experimental results, but the detection results need to be processed manually and the accuracy of automatically identifying defects and discharge types is not high enough, and the detection speed is slow. As a widely used classification and recognition algorithm, DBN can effectively distinguish different samples. This article will study the application of DBN to the detection of UHF PDs, and propose an improved DBN algorithm for online detection of PDs of GIS equipment, discover and solve internal insulation problems and fault types in advance, and provide valuable experience for the future improvement and promotion of automatic online detection system.

2. UHF PD system

2.1. Principle of UHF PD

In the event of a PD failure of GIS equipment, the pulse current generated at the discharge can excite high-frequency electromagnetic waves inside the equipment. The frequency of electromagnetic waves can reach above GHz, also called UHF electromagnetic waves. UHF PD detection technology is through UHF sensors to detect the UHF electromagnetic waves excited by the pulse current to achieve PD detection [9]. The frequency range of UHF electromagnetic wave is between 300MHz and 3GHz. Because the interference electromagnetic wave generated by the surrounding power frequency current has a low frequency, the UHF detection method has the obvious advantages of anti-interference and high sensitivity, so, it is widely used in the PD detection of user GIS equipment. Figure 1 is a schematic diagram of UHF PD. Common UHF PD types are mainly divided into free metal particle discharge, creeping discharge, internal air gap discharge, and corona discharge.
2.2. **UHF PD detection system**

The overall workflow of the GIS PD detection system is shown in Figure 2. First, the UHF sensor installed in the GIS equipment starts to detect, output the UHF signal, and the high-speed signal acquisition system performs the data collection, and then judge whether the collected signal contains UHF signal, if there is no UHF signal, then repeat UHF detection and data collection, if there is a UHF signal PD signal in the collection, then the type of the PD signal is identified and judged, and finally, the defects and failures detected in the GIS equipment are maintained according to the identification results.

3. **UHF PD detection method based on improved DBN**

3.1. **DBN principle**

After the UHF signal is detected, it takes a long time and low efficiency to manually judge the type of PD. The DBN is used to automatically classify the UHF PD signal, which realizes the rapid classification and evaluation of the UHF PD type. DBN can perform unsupervised training by stacking multiple Restricted Boltzmann Machines (RBMs) to extract deep features from complex data. However, if you want to classify the data, you need to add a classifier to the top layer of the stack to complete the direct classification of the data and form a complete DBN model [10]. Figure 3 is a schematic diagram of the basic structure of DBN.

![Figure 1. Principle of UHF PD.](image1)

![Figure 2. Operation principle of PD detection.](image2)

The training of DBN can generally be divided into two stages: unsupervised training and supervised fine-tuning [11]. The training of DBN is unsupervised. It directly maps the data from input to output, and learns the characteristic information in the complex original signal. This is also the advantage of DBN. Training RBM layer by layer evolves the DBN into a shallow neural network, which greatly reduces the computational complexity [12].
3.2. Improvement of activation function

If there are only fully connected operations and linear convolutions in a neural network, even if the depth of DBN is increased and multiple iterations are performed, the final output will still be a linear function of the input, and it is impossible to model and classify nonlinear data in the actual environment. However, after adding the activation function, the neural network has the ability of nonlinear mapping learning. The activation function here is generally a nonlinear increasing function. Therefore, in order to make the neural network can be applied to many nonlinear models and model non-linear data, it must have a nonlinear activation function [13]. How to choose the activation function, there is no final conclusion. In actual use, it is necessary to consider the pros and cons of different activation functions based on actual conditions and experience, and to verify the final selection through experiments. Commonly used activation functions generally include Sigmoid, ReLU, and tanh. Their function images are shown in Figure 4. The expressions are as follows:

\[
\text{ReLU} = \max(0, x) \quad (1)
\]

\[
\tanh = \tan^{-1}(x) \quad (2)
\]

\[
\text{Sigmoid} = \frac{1}{1 + e^{-x}} \quad (3)
\]

This article uses the Sigmoid function as the activation function. Taking into account the use of Sigmoid, when reverse fine-tuning the error gradient, it is necessary to derive, and when the sigmoid function is close to the saturation zone, the reciprocal is very close to 0. This situation will cause the loss of feature information, and the training and feature extraction of DBN cannot be completed. Analyzing the input x of the sigmoid function, it is found that the range of x is between -20 and 20. The sigmoid function can be stretched by adding coefficients to the sigmoid function. The reciprocal of the function between -20 and 20 is far away from the x axis. In order to prevent the disappearance of the gradient, and if the sigmoid function is stretched too large, the function will be closer to the linear function between -20 and 20, which reduces the nonlinear learning ability of DBN, so it is...
necessary to adjust the self. The coefficient of the variable $x$ is changed, and Formula (3) becomes Formula (4).

$$Sigmoid = \frac{1}{1 + e^{-\alpha x}}$$ (4)

Figure 5 is a graph of the DBN classification error as $\alpha$ changes from 0 to 2. It can be seen from the figure that the classification error of DBN decreases first, and then increases. When $\alpha$ is between 0.5 and 0.8, the classification error of DBN is the smallest and basically remains at 0.063. Therefore, the use of an improved activation function can effectively reduce the classification error of DBN. In this paper, the intermediate value $\alpha=0.7$ will be selected.

![Figure 4. Graph of DBN classification error.](image)

![Figure 5. Comparison of prediction results and actual classification results at $\alpha=0.7$.](image)

### 3.3. Modeling of UHF PD classification based on DBN

| Table 1. The solar intensities in different time periods. |
|---------------------------------------------------------|
| PD type/mm | Data type |
|------------|-----------|
| Free metal particle discharge | 10000000000 |
| Creeping discharge | 0100000000 |
| Internal air gap discharge | 0010000000 |
| Corona discharge | 0001000000 |

The PD signals of four characteristics: free metal particle discharge, creeping discharge, internal discharge and corona discharge are measured respectively. Each PD is measured 100 times, and a data set is extracted. The signals of the same discharge type are classified into one category. There are 4 types of PD signals, so they are divided into 4 categories. Since the number of data types is equal to the number of output nodes, there are 4 PD types in the model, so the number of output nodes is set to 4. And the number of hidden layer nodes is set to 200, the number of iterations is set to 50, the learning rate and initial momentum settings are kept as defaults, respectively 0.1 and 0, and the coefficient of the excitation function is set to 0.7. During training, 340 groups were randomly selected from 400 data sets as training, and the remaining 60 data sets were used as tests.
When $\alpha$ is 0.7, after training, the 60 sets of random data in the test data set are tested, and the final DBN classification error is 0.0333, and the classification accuracy rate reaches 96.7%. The actual output of the training sample is basically consistent with the expected value. The final predicted classification results and actual classification results of 60 sets of test data are shown in Figure 5. Table 2 shows the recognition results of UHF PD models by Li Ya and Cui Haoyang on 4 different neural network methods [14]. This paper uses the neural network method based on DBN to identify the type of UHF PD with an accuracy rate of 96.7%. Compared with other neural network methods, it can complete the identification of the type of PD better.

Table 2. Identification of UHF PD models using four different neural network methods.

| PD recognition model | Type of discharge | Misidentification number | Accuracy/% | Average accuracy /% |
|----------------------|-------------------|--------------------------|------------|--------------------|
| BP network           | Metal spikes      | 1                        | 85.71      | 77.74              |
|                      | Particle discharge| 2                        | 60.00      |                    |
|                      | Floating discharge| 1                        | 87.50      |                    |
| LVQ network          | Metal spikes      | 2                        | 77.78      |                    |
|                      | Particle discharge| 1                        | 83.33      | 87.04              |
|                      | Floating discharge| 0                        | 100.00     |                    |
| K cross-validated LVQ network | Metal spikes | 1 | 88.89 | 89.53 |
|                      | Particle discharge| 1 | 94.00 | |
|                      | Floating discharge| 0 | 85.71 | |
| MEA optimizes LVQ network | Metal spikes | 0 | 100 | 96.30 |
|                      | Particle discharge| 0 | 100 | |
|                      | Floating discharge| 1 | 88.89 | |

4. Experimental verification

4.1. 110kV cable-GIS terminal insulation internal air gap defect detection

UHF PD detection system was applied to a 500kV substation 110kV three-phase cable-GIS terminal equipment for PD detection. It was found that the cable terminal had a PD signal, and the A, B, and C three-phase cable terminals could all detect the PD signal, the amplitude of the PD signal of phase A is the largest. The measured spectra are shown in Figure 6.

![Detection spectra of the cable-GIS terminal equipment.](image)

Figure 6. Detection spectra of the cable-GIS terminal equipment.

Import the peak detection data into DBN for automatic detection and classification, and the result is 3, which is automatically classified as internal air gap discharge through DBN detection. According to the amplitude comparison method, it can be known that the PD position of the GIS terminal is at A-phase. After replacing the A-phase cable terminal and re-testing the UHF PD, the abnormal signal disappeared. Laboratory PD testing was carried out on the A-phase cable terminal removed after replacement, and it was found that there was an abnormal signal of UHF PD. CT was used to detect the A-phase cable GIS terminal, and it was found that there was an obvious air gap between the epoxy
casing and the epoxy resin. By replacing the A-phase cable terminal in time, accidents were avoided. For the problems detected in the phase A cable, CT was used to scan the epoxy casing, and it was found that there was a clear gap between the epoxy casing and the metal terminal of the epoxy casing. The CT scan is shown in Figure 7 below.

![Figure 7. Scanning of defect section of epoxy casing.](image1)

![Figure 8. Air cavity defect of epoxy casing.](image2)

In order to further determine the defects at the epoxy casing, the epoxy casing was cut open and it was found that there is indeed an air cavity between the epoxy casing and the metal terminal. The air cavity is about 2 cm wide and 0.5 cm high. The CT scan showed the same position. Figure 8 is a photo of the epoxy casing air cavity defect.

4.2. Detection of discharge defects in the internal knife gate of 66kV GIS

When the UHF PD detection method was used to conduct routine live detection work on a 66kV substation GIS, the UHF PD detector was used to find that there was obvious abnormal discharge signal in the 204-3 C-phase knife gate air chamber on the 66kV side of the #4 main transformer. UHF PD detection was performed on the 204-3 knife gate, and the resulting spectrum is shown in Figure 9.

![Figure 9. Detection spectra of the 204-3 knife gate.](image3)

![Figure 10. Insulator, GIS inner wall dust and fork ablation diagram.](image4)
Import the peak detection map data into DBN for automatic detection and classification, and the result is 1, that is, it is automatically classified as a metal particulate discharge through DBN detection. After disassembly, it was found that the equipotential spring at the connection between the knife gate operating fork and the moving contact in the 204-3 C-phase knife lock air chamber was not installed, resulting in poor contact between the fork and the moving contact. There are obvious burn marks on the shift fork, and the transmission insulator is covered with discharge dust, as shown in Figure 10. Immediately, the ablated shift fork was replaced, and the insulator and the entire air chamber were cleaned. Retest after treatment, and the abnormal signal disappeared.

5. Conclusions
This paper improves the DBN method and applies it to the online detection of UHF PD detection system, which greatly accelerates the classification detection efficiency, and the detection results match the actual situation completely. It solved the problem of slow, low efficiency and difficult calculations of manual processing of UHF PD data. The UHF PD system designed in this paper has great practical application value. It realizes the early prevention and maintenance of GIS equipment failures, greatly reduces the failure rate of GIS equipment, and contributes to the construction of a strong smart grid in my country. It is of great significance.

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