Stage Recognition of Surface Discharge in Oil-Impregnated Paper Based on Convolutional Neural Network

Yuanxiang Zhou, Jianning Chen, and Yongyin Li

Abstract The stage recognition of surface discharge in oil-impregnated paper is of great significance to the safe and reliable operating of power transformer and the construction of digital twin system. Therefore, a convolutional neural network (CNN) method is proposed in this paper to identify the development stages of surface discharge. Firstly, the surface discharge experiment of oil-paper insulation was carried out by step-up voltage method. Then, according to the difference of phase-resolved partial discharge (PRPD), the surface discharge process could be divided into various stages. Finally, CNN was adopted to identify different stages of surface discharge, compared with support vector machine (SVM) and back propagation neural network (BPNN) based on 24-dimensional feature extraction. The results show that after 100 iterations, the recognition accuracy of CNN on surface discharge stage reaches 99.17%, while the overall accuracy of SVM and BPNN is only 91.04% and 87.29%, respectively. The CNN model proposed in this paper can automatically and effectively identify the PRPD patterns of different stages of surface discharge, with a higher recognition accuracy than the traditional methods such as SVM and BPNN.

Keywords Convolutional neural network · Oil-paper insulation · Surface discharge · Stage identification

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1 Introduction

Oil-paper insulation system is the main part of oil-impregnated power transformer insulation. In the case of damp, mechanical deformation, partial discharge is easy to occur on the oil-paper interface. Surface discharge is considered as one of the most serious fault types of transformer due to its fast development speed and large insulation damage [1]. Surface discharge at different stages has different damage degrees to oil-paper insulation, so it is of great significance to carry out identification of development stages of surface discharge for safe operating of transformers and construction of digital twin [2, 3].

Scholars at home and abroad have carried out extensive research on the identification of partial discharge. Zhou divided the partial discharge stages according to the discharge characteristics, the gradient of the discharge pattern and other fingerprint parameters, combined with the gas production characteristics [4]. Li adopted the genetic optimization support vector machine (SVM) algorithm with feature selection to identify the three stages of surface discharge [5]. Sun and other scholars [6, 7] extracted 29 statistical parameters of phase-resolved partial discharge (PRPD). And the probabilistic neural network (PNN) algorithm was used to identify the development stages of oil-paper insulation discharge with different aging degrees. Compared with back propagation neural network (BPNN) model, it was found that its recognition accuracy was higher. Ren used a multi-spectral ratio feature and deep neural network (DNN) model to classify the severity of surface discharge with an accuracy of over 93% [8].

Most of the studies used the feature from artificial extraction to identify the stage of surface discharge of oil-paper insulation, requiring the combination of one or several aspects of statistical characteristics, which had a certain subjectivity and could not reflect all the characteristics of each stage of surface discharge, leading to poor generalization performance. In this paper, the convolutional neural network (CNN) is adopted to automatically extract the features from the PRPD pattern, and identify the different stages of surface discharge. The recognition accuracy is compared with that of traditional methods such as SVM and BPNN with manual feature extraction.

2 Experiment

2.1 Sample Preparation

Karamay KI25X was selected as the experimental insulating oil, and its processing process is as follows. The transformer oil is pumped into a 40 °C vacuum oil filter for filtering, drying and degassing, and impurities such as particulate matter and moisture in the oil are fully removed. The filtered transformer oil meets the relevant provisions in CIGRE 12.17, and then it is put into a beaker that is fully washed and dried by anhydrous ethanol and deionized water, and dried for more than 48 h in a

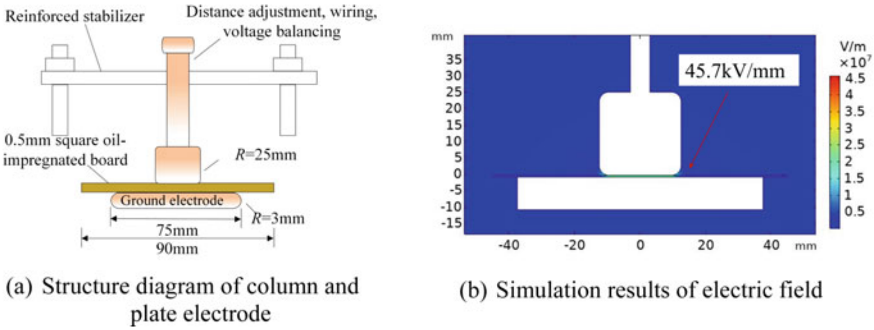

Fig. 1 The structure diagram of column and plate electrode and its simulation results of electric field

vacuum drying oven. Carl Fischer instrument was used to measure the moisture and ensure that moisture content in oil meets national standards. The insulating paper of the experiment is 0.5 mm Nantong Zhongling insulating paper.

The processing process of the oil-impregnated paper is as follows. First, the insulating paper is uniformly placed in a vacuum drying oven with temperature of 105 °C and pressure of 100 Pa for 48 h. Then, transformer oil is soaked in the insulating paper at 80 °C in vacuum. After full impregnated, it was cooled to room temperature naturally, and then transferred to a vacuum oven to dry for more than 48 h. Before the experiment, the physicochemical test of the oil-impregnated board is carried out, satisfying the requirements of IEC 60641-2.

2.2 Defect Simulation

The column plate electrode is selected as defect model according to IEC 60243-1. Its height and diameter are both 25 mm. The schematic diagram of its structure and the simulation results of electric field are shown in Fig. 1. Between the high voltage electrode and the ground electrode of the defect model was 0.5 mm square oil-impregnated paper. Under the strong vertical electric field, there exits both surface discharges generated by parallel components along the oil-paper interface and oil gap discharges caused by vertical components. The maximum electric field was located at the junction of high voltage electrode, oil-impregnated paper and oil.

2.3 Construction of Partial Discharge Experimental Platform

In order to obtain PRPD pattern of different stages of surface discharge in oil-paper insulation under column and plate defect, the experimental platform was built, as shown in Fig. 2, which met IEC 60270 partial discharge experimental standards. The experimental circuit consists of three parts, including the power supply part, sample loop part and signal acquisition part. The power supply mainly includes the programmable signal generator AFG 3011C and the high voltage power amplifier Trek model (50 kV/12 mA). The programmable signal generator is adopted to generate voltage waveform, and the high voltage power amplifier will amplify the generated signal at a fixed gain of 5000:1 and apply it to the sample. In the sample loop part, the sample to be tested is directly connected with the coupling capacitance and the measured impedance, which is connected with the coupling capacitance in series to convert the pulse current signal into the voltage signal. Signal acquisition part collect partial discharge signals from the measurement impedance through the partial discharge measurement unit MPD600, then transmitting data to the PC terminal for analysis and processing. Digital oscilloscope is used to monitor the output waveform of high voltage power amplifier. All components in the circuit are smoothed to prevent additional partial discharge.

After each calibration or sample replacement, it is necessary to carry out no-load experiment to ensure that no discharge occurs when loop voltage is boosted to 35 kV, with noise signal less than 8pC.

The applied voltage method of surface discharge experiment is stepped voltage boost, and the typical waveform is shown in Fig. 3. The step-up method can ensure that more experimental data can be obtained in limited time. Before the experiment, it is necessary to measure the initial discharge voltage. During the PRPD experiment, the boost step and time interval remain unchanged. The step size is 0.4 kV AC and the interval is 20 min, and the PRPD pattern is collected.

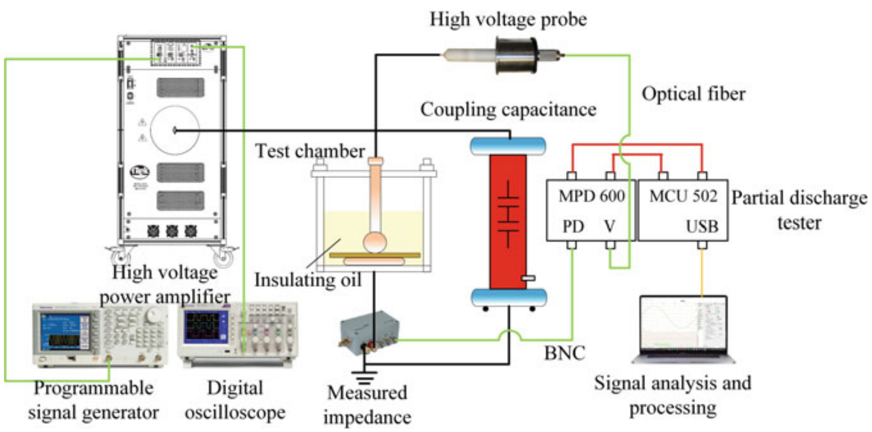

Fig. 2 Experimental platform of partial discharge

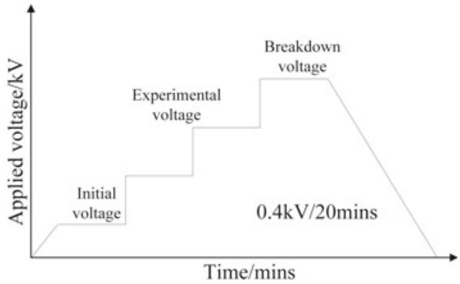

Fig. 3 Applied voltage waveform

2.4 PRPD Pattern

According to the characteristics of PRPD pattern, the development process of surface discharge can be divided into the initial stage, the development stage, and the stage of near breakdown stage.

The PRPD pattern at the initial stage of surface discharge is shown in Fig. 4a. The discharge phase is mainly distributed in 45°–90° and 210°–270°. The positive half-cycle discharge pulse is evenly distributed between 0 and 3000pC, while the majority discharge under negative polarity is lower than 500pC. The discharge is mainly caused by high voltage electrode ionizing impurities and water in the oil, so the quantity is small and the development is slow, without large discharge appearing.

The PRPD pattern of the development stage of surface discharge is shown in Fig. 4b. The PRPD pattern presents a peak-like distribution, and the discharge amplitude slightly lags behind the peak applied voltage. Corona discharge at initial stage evolves into discharge along the oil-paper interface, and the discharge phase is mainly distributed in 30°–120° and 180°–270°, significantly extended compared with the discharge phase at initial stage. The maximum discharge quantity is also greatly increased to 10nC. The distortion electric field near the high voltage electrode cracks the transformer oil into H_2, CH_4 and other small molecules, further aging the insulation oil and aggravates the damage degree of oil-paper insulation.

The PRPD pattern near the breakdown stage of surface discharge is shown in Fig. 4c. The PRPD pattern is shaped like 'rabbit ears', that is, the front end of the discharge cluster protrudes, resembling rabbit ears, and there are many large value discharge pulses near the voltage peak. The discharge is distributed in the range of 0°–360°, and the discharge quantity increases to tens of nC. The discharge channel is formed perpendicular to the oil-impregnated paper, and the insulation is further aged. The aging of the paper and the growth of the distorted electric field at the defect promote each other, accelerating the development of discharge, finally leading to breakdown.

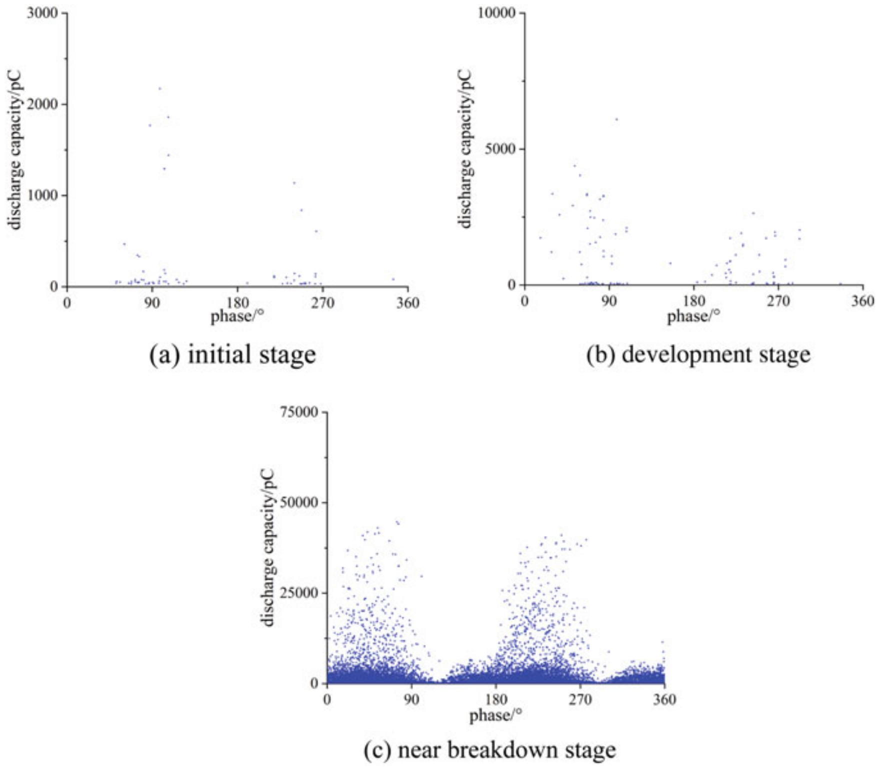

Fig. 4 PRPD pattern of surface discharge on various stages

3 Pattern Recognition

3.1 Model Building

In this paper, two-dimensional convolutional neural network [9] is used for PRPD pattern recognition, whose basic structure includes input layer, convolutional layer, pooling layer, fully connected layer and output layer. The convolutional layer extracts feature information from the PRPD pattern and forms a new feature subgraph. Its convolutional kernel is essentially a filter to obtain features such as texture and edge of the image. Pooling layer is also known as the lower sampling layer, which is used to reduce the number of output parameters and represent the image with higher level features. As a classifier, the fully connected layer receives the features extracted after convolution pooling and maps them to a specific label such as 0, 1, and 2, corresponding to initial stage, development stage and near breakdown stage, respectively. Finally, the output is mapped to the probability distribution of 3 types of stage by the Softmax layer. The convolutional neural network structure established in this paper

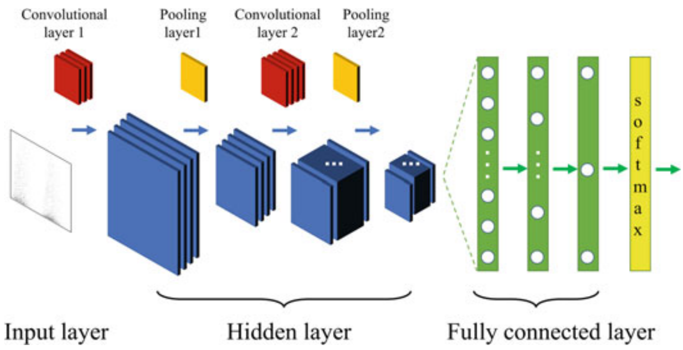

Fig. 5 Structure of convolutional neural network

is shown in Fig. 5, which includes 1 input layer, 2 convolutional pooling layers, 3 fully connected layers and 1 output layer. Among them, the first convolutional layer has a total of 4 convolutional kernels, and the second convolutional layer has a total of 16 convolutional kernels, with the size of 3 × 3. Maximum pooling was adopted. The number of units in the three fully connected layers is 96, 24 and 3, respectively.

3.2 Network Training

A total of 2400 PRPD pattern of different stages of surface discharge under column and plate defects were obtained by experiments, including 400 at the initial stage, 1000 at the development stage and 1000 at the near breakdown stage. 80% of the data is for training and 20% for testing.

The corresponding model is built in the server for training and testing. In the training process of convolutional neural network, cross entropy is used as a loss function to evaluate the training error, and the random gradient descent method is used to update the parameters. The training times are 100 times. Each iteration traverses the pictures of the training set once, and 20 iterations are carried out in each training cycle, for a total of 5 cycles. The initial learning rate is set at 0.001, with a 50% drop per cycle. The deep learning framework used in this paper is Pytorch and the programming language is Python3.9.

3.3 Recognition Accuracy Comparison

In order to evaluate the performance of the CNN model in stage recognition of surface discharge in oil-impregnated paper, its recognition accuracy was compared with the traditional machine learning models such as SVM and BPNN [10].

Statistical features extracted by SVM, BPNN and other methods include skew K_u, steepness S_k, peak number, asymmetry A_{sy}, correlation coefficient C_c, etc., as shown in Table 1. The definitions of each statistical parameter are detailed in literature [11].

The recognition accuracy of three different models, CNN, SVM and BPNN, is shown in Fig. 6. According to Fig. 6, the recognition accuracy of CNN for each stage is higher than that of BPNN and SVM classifiers. After 100 iterations, the overall average recognition accuracy is 99.17%, while that of SVM and BPNN are 91.04% and 87.29%, respectively.

Since the features extracted by SVM and BPNN are based on the 24-dimensional statistical features of q_{max}-φ, q_{ave}-φ, n-φ pattern, which cannot accurately reflect all the statistical features of the pattern, resulting in worse performance in the stage identification of surface discharge. In the process of model training, convolutional neural network will automatically extract the features of the pattern. It can intelligently adjust the weight contribution of different spatial positions and different feature types to classification results, which has certain advantages over traditional manual feature extraction.

Table 1 Statistical parameters of three characteristic pattern

Statistical characteristics	q_{max}-φ		q_{ave}-φ		n-φ	
	+	−	+	−	+	−
K_u	√	√	√	√	√	√
S_k	√	√	√	√	√	√
Peaks	√	√	√	√	√	√
A_{sy}	√		√		√	
C_c	√		√		√	

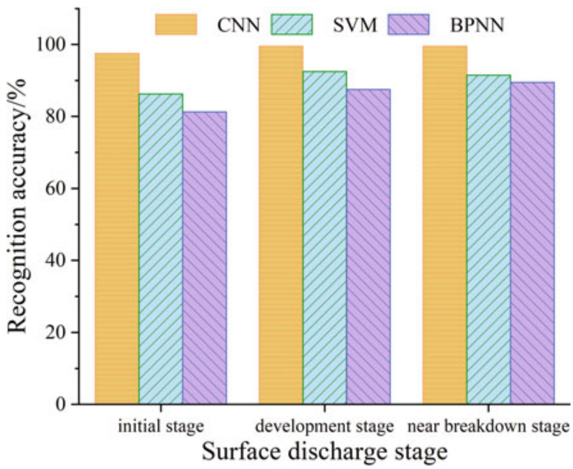

Fig. 6 Comparison of recognition accuracy of different models

4 Conclusion

In this paper, by comparing the characteristics of PRPD pattern of oil-paper insulation along surface discharge in different development stages, a recognition method of oil-paper insulation along surface discharge development stage based on convolutional neural network is proposed. The recognition accuracy of this method is compared with SVM, BPNN and other methods to extract the statistical parameters of feature pattern, and the superiority of this method is verified. In the process of model training, convolutional neural network can automatically extract the features of the pattern and intelligently adjust the weight contribution of different spatial positions and different feature types in the pattern to classification results. Therefore, CNN-based classifier has more advantages than SVM and BPNN based on manual feature extraction. The overall average classification accuracy can be improved from 91.04% and 87.29% to 99.17%. Therefore, the convolutional neural network model proposed in this paper can provide effective method support for stage identification of transformer surface discharge.

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