Partial discharge development stage division based on multi-classifier fusion

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Abstract. The oil-paper insulation air gap discharge experiment was carried out by the step-up method, and the 29-dimensional discharge characteristic parameters were extracted. According to K-means clustering, the partial discharge development stage is divided into four stages: initial discharge stage, discharge development stage, discharge stability stage and near breakdown stage. The three basic classifiers of random forest, support vector machine and back propagation neural network are trained by the credibility-based adaptive weighted voting algorithm to train a new fusion classifier. Compared with the traditional classification fusion device, the proposed classifier fusion model can effectively improve the accuracy of the identification of the discharge development stage, up to 87.5% or more.

1. Introduction
Power transformer is one of the most important equipments in power system. More than 80% of faults in power transformer are caused by insulation failure according to statistics [1-3]. The common insulation mode of Power transformer is oil-paper insulation and air gap discharge is the major form of partial discharge in oil-paper insulation. Due to damp, electrode burr, mechanical deformation and other reasons, it is easy to make transformer partial field intensity too high, leading to partial discharge and then affecting the stability of the entire power system operation [4-5]. Once an accident causes a large-scale blackout, it will bring huge economic losses. At present, partial discharge detection on-line has become an important part of smart grid. Therefore, it is of great significance to identify the development stage of partial discharge in oil-paper insulation.

It is one of the research hotspots in recent years to reflect the development degree of transformer oil-paper insulation defects by partial discharge characteristic parameters. Its response to sudden failure has high sensitivity, which can make up for the lack of on-line detection of oil chromatographic analysis. Therefore, the detection method of partial discharge has attracted the attention of many scholars. The research on partial discharge at home and abroad mainly focuses on four aspects: discharge characteristics, pattern recognition, aging assessment and development stage diagnosis. Some achievements have been made in the identification of the development stage of partial discharge. Reference [6] classifies the development stages of air gap discharge by cluster analysis. Wavelet neural network model was established to identify the development stage of discharge, and the results were
compared with those of system clustering. Reference [10] carried out step-by-step boost test on the surface discharge model until the cardboard was broken down. It is considered that the whole process can be divided into four stages: larger discharge amplitude, smaller discharge amplitude, sudden increase of discharge amplitude, and the eve of breakdown. And clustering method is used to identify the development stage of discharge. Reference [11] divides the surface discharge into three stages: the initial stage, the development stage and the pre-breakdown stage by analyzing the discharge characteristics, the discharge pattern and the scanning electron microscopic pattern in the discharge process. The genetic optimization support vector machine algorithm is used to identify the development stage of surface discharge. In reference [12], the partial discharge characteristics of air gap and electrical branch channels are studied. It is found that there is a close relationship between air gap discharge and Weibull characteristic parameters of partial discharge pulse amplitude.

In summary, most studies use a single classifier to identify the development stage of discharge. However, a single classifier usually processes data features from a certain point of view and can’t fully analyze the sample to be processed, so the recognition effect is not good. Therefore, the output of the multi-classifier is fused by algorithm to get the final recognition result in order to realize the complementary advantages of each classifier in this paper.

2. Experiment of oil-paper insulation air gap discharge

According to the IEC 60243 standard, a typical air gap discharge defect model is fabricated. The electrode material is made of brass, whose surface is polished. Xinjiang Karamay No. 25 mineral insulating oil is used in this experiment, which is degassed, dried, filtered. And insulated cardboard produced by Shenyang Transformer Factory is burr-free and flat on the surface. Three 80mm × 80mm × 2mm insulation paperboards bonded with insulating glue form an air gap discharge model. The intermediate layer of insulating paperboard was cut through a hole having a diameter of 20 mm. The air gap discharge experimental device model is shown in Fig.1. The insulating paperboard was vacuum dried for 2 days at 90 °C / 50 Pa, and then vacuum immersed for 5 days at 80 °C / 50 Pa.

![Air gap discharge experimental device](image)

**Figure 1.** The air gap discharge experimental device.

The pulse current method is used to measure the air gap discharge of the oil-paper insulation and the JFD-2000 conventional pulse local discharge instrument is used to save the signal of the experimental process, like this is shown in Fig.2. The discharge starting voltage of the experimental sample was determined to be 9.0 V after repeated experiments. The step-up boost mode was used in this experiment that starts at the starting voltage and boosts 1kV every 5 minutes until the sample breaks down. The discharge pattern and characteristic parameters of the entire discharge process are recorded for subsequent processing and analysis.
3. Discharge development stage division

3.1. Characteristic parameter of PRPD

Here is how to display a pop-up window from which to select and apply the AIP Proceedings template paragraph styles. In this paper, the phase resolved partial discharge (PRPD) spectrum is studied, including four two-dimensional maps of $H_{\text{qmax}}(\phi)$, $H_{\text{qs}}(\phi)$, $H_{\text{n}}(\phi)$, and $H_{\text{n}}(q)$. And 29 statistic parameters were extracted, such as kurtosis ($k_u$), skewness ($s_k$), peak ($p_{\text{peak}}$), asymmetry ($a_{\text{sy}}$), correlation coefficient ($C_c$), Weibull distribution parameters $\alpha$ and $\beta$. As shown in Tab.1, the definition and calculation expression of each parameter can be found in the reference.

### Table 1. Statistical characteristic parameters of PRPD.

| Parameter | $H_{\text{qmax}}(\phi)$ | $H_{\text{qs}}(\phi)$ | $H_{\text{n}}(\phi)$ | $H_{\text{n}}(q)$ |
|-----------|--------------------------|------------------------|----------------------|------------------|
| $k_u$     | +                        | No -                   | +                    | -                |
| $s_k$     | +                        | No -                   | -                    | +                |
| $p_{\text{peak}}$ | +                     | No -                   | +                    | -                |
| $a_{\text{sy}}$ | -                     | +                      | +                    | -                |
| $C_c$     | -                        | No -                   | +                    | -                |
| $\alpha$  | -                        | -                      | No -                 | +                |
| $\beta$   | -                        | -                      | -                    | No -             |

Note: “+” is the positive half cycle of the power frequency; “-” is the negative half cycle of the power frequency.

3.2. K-means clustering

3.2.1. The principle of K-means. The K-means algorithm is one of the most widely used clustering algorithms [13]. The algorithm needs to be given the dataset $X$ of $n$ objects and the number of clustering subsets $k$ to be generated, and the clustering target is clustered by high similarity within clusters and low similarity between clusters. The sample data set $X=(x_1,x_2, \ldots,x_n)$ is assumed to contain $k$ cluster subsets, $k<n$. Define sample $x_i=(x_{i1},x_{i2},\ldots,x_{id})$ and sample $x_j=(x_{j1},x_{j2},\ldots,x_{jd})$. The similarity between the samples $x_i$ and $x_j$ is represented by the Euclidean distance $d(x_i, x_j)$:

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{d} (x_{ik} - x_{jk})^2}$$

(1)

The error squared criterion function $E$ is used as the criterion for judgment:

$$E = \sum_{j=1}^{k} \sum_{p \in x_i} \|p - m_j\|^2$$

(2)
In Equation 2, the \( i \)-th cluster subset is represented by \( X_i \), and the \( i \)-th cluster subset center is represented by \( m_i \). The smaller the \( E \) value is, the better the criterion function for evaluating the clustering performance is, the more compact the cluster is, and the more independent the clusters are.

The algorithm process is as follows: Firstly, set \( k \) cluster subsets to determine an initial cluster center for each cluster. Secondly, assign the samples in the sample set to the nearest neighbor cluster according to the principle of minimum distance. Thirdly, Use the sample mean in each cluster as the new cluster center. Finally, repeat steps 2 and 3 until the cluster center no longer changes.

3.2.2. The division process of air gap discharge based on K-means. When receiving the paper, we assume that the corresponding authors grant us the copyright to use the paper for the book or journal in question. Should authors use tables or figures from other Publications, they must ask the corresponding publishers to grant them the right to publish this material in their paper. The partial discharge process of oil-paper insulation is a random process, and it is very difficult to accurately determine what discharge stage the partial discharge is in. The partial discharge process of oil-paper insulation is a random process, and it is very difficult to accurately determine what discharge stage the partial discharge is in. However, it is feasible to divide the whole discharge process into several stages according to the variation law of the partial discharge characteristics in different discharge stages. In this paper, a partial discharge signal was collected every 1 min at the beginning of the initial discharge of the air gap discharge test during each experiment. A total of 68 different moments, \( t_1, t_2...t_{68} \), were collected from the initial discharge to the near-breakdown state.

| Classification  | Sample Number |
|-----------------|---------------|
| First Class     | \( r_1, r_2, r_3, r_4, r_5, r_6, r_7, r_8, r_9, r_{10}, r_{11}, r_{12}, r_{13}, r_{14}, r_{15}, r_{16}, r_{17}, r_{18}, r_{19}, r_{21}, r_{22}, r_{23}, r_{24}, r_{25} \) |
| Second Class    | \( r_{26}, r_{27}, r_{28}, r_{29}, r_{30}, r_{31}, r_{32}, r_{33}, r_{34}, r_{35}, r_{36}, r_{37}, r_{38}, r_{39}, r_{40}, r_{41}, r_{42}, r_{43}, r_{44}, r_{45}, r_{46} \) |
| Third Class     | \( r_{47}, r_{50}, r_{51}, r_{52}, r_{53}, r_{54}, r_{55}, r_{56}, r_{57}, r_{58}, r_{63} \) |
| Fourth Class    | \( r_{59}, r_{60}, r_{61}, r_{62}, r_{64}, r_{65}, r_{66}, r_{67}, r_{68} \) |

The classification results of Tab.2 can be obtained. The discharge signals of sample numbers \( r_1~r_{25} \) are divided into one class. The discharge signal at this stage is from scratch, corresponding to the initial discharge stage. Then, during the period from \( r_{26}~r_{46} \), the amount and the number of discharge increased significantly, and a weak discharge sound appeared, corresponding to the discharge development stage. After that, during the period from \( r_{42}~r_{58} \), the discharge amount is relatively stable, and the amplitude and number of discharges do not change much. This stage is divided into a discharge stabilization stage. Finally, during the period from \( r_{59}~r_{68} \), the amount and the number of discharge increased again with the sound of a discharge, which did not last long until a loud bang occurred because the cardboard was penetrated. Therefore, this stage is divided into adjacent breakdown stage.

4. Air gap discharge development stage identification
A classification model with single feature information is difficult to perform very well. A single classifier usually processes the action features from a certain angle, which makes it impossible to fully understand the samples to be processed, so that the recognition effect is not good [14, 15]. Support vector machines (SVM), random forest classification (RFC), and error back propagation neural networks (BPNN) are used in order to achieve complementary advantages between the various classifiers. The output of the multi-classifier is obtained by the fusion algorithm to obtain the final classification result.

4.1. Multi-classifier fusion algorithm
SVM offers many advantages in solving nonlinear and high-dimensional features, especially in solving small sample problems. It is a classifier model, whose principle is to find a hyperplane to segment the sample and split the two types. In this paper, a one-to-one classification method is used to construct 6 SVM classifiers in the training set, and 6 discriminant functions can be obtained.
RFC is a combined classification model consisting of many decision tree classification models. Given a dependent variable, each decision tree classification model selects the best classification result by one vote. The majority of voting decisions are made to determine the final classification. The number of trees selected is 240.

BPNN is mainly divided into two stages: the forward process and the back propagation process. A three-layer neural network is employed, which is trained by the gradient descent function. The number of nodes is 29 in the input layer, the number of nodes is 17 in the hidden layer, and the number of nodes is 4 in the output layer. By introducing the decision-related information of the classifier, the weights are adaptively assigned to each classifier, so that the classification accuracy becomes more accurate.

\[
\lambda_i = W(x_j)W(x_{ij})
\]

\[
\bar{x}_j = \frac{\sum_{i=1}^{n} \lambda_i}{n}
\]

\[
\delta_{ij} = \begin{cases} 
\bar{x}_j, & \lambda_{ij} = \max \sum_{i=1}^{n} \lambda_{ij} \\
1 - \bar{x}_j, & \lambda_{ij} < \max \sum_{i=1}^{n} \lambda_{ij}
\end{cases}
\]

In Equation 3, \(\lambda_i\) is the credibility of the \(j^{th}\) class of the \(i^{th}\) base classifier; \(W(x_i)\) is the number of \(j^{th}\) sample; \(W(x_{ij})\) is the number of samples of the \(j^{th}\) class after the \(i^{th}\) base classifier. \(\bar{x}_j\) is expressed as the average credibility of the \(j^{th}\) class successfully classified after the \(i^{th}\) base classifier. \(\lambda_{ij}\) is the number of the \(j^{th}\) class successfully classified after the \(i^{th}\) base classifier. \(\delta_{ij}\) is the fusion weight of the \(j^{th}\) base classifier of the \(i^{th}\) class.

The cumulative probability is calculated by weighting the recognition posterior probability \(p_{ij}\) of each sample with each base classifier.

\[
T_j = \sum_{i=1}^{n} \delta_{ij} p_{ij}
\]

\[
\text{class} x = \arg \max \sum_{j=1}^{n} T_j
\]

In Equation 5, \(T_j\) is a different category of fusion weights. The class to which the sample belongs is determined by the maximum probability of fusion by decision. When the same is judged, the weight of the \(b\) sub-classifiers that judge the error is decremented by the penalty factor \(\varepsilon\). According to the size of the posterior probability, the fusion weights of the \(b\) classifiers with larger posterior probabilities of the basic classifiers are respectively added \(\varepsilon\). The sample is judged to be completely wrong by all classifiers, which is noise and discarded. Traverse the samples to get the final fusion weight.

4.2. Analysis of results

In many experiments, a total of 1360 valid samples were collected, of which 960 were used for training and the remaining 400 were tested. The recognition accuracy of the test samples of the different basic classifiers is shown in Table 3 for the discharge development stage.

| Different Stage                | SVM (%) | RFC (%) | BPNN (%) |
|-------------------------------|---------|---------|----------|
| initial discharge stage       | 77.0%   | 54.1%   | 78.4%    |
| discharge development stage   | 61.6%   | 77.4%   | 58.6%    |
| discharge stabilization stage | 72.1%   | 60.0%   | 68.5%    |
| adjacent breakdown stage      | 67.2%   | 58.6%   | 79.3%    |
There are significant differences in the recognition rates of different basic classifiers. It can be seen that using only a single classifier does not have good classification capabilities. For example, the overall performance of BPNN is higher than the other two classifiers, but the recognition result in the discharge development stage is the lowest among the three classifiers. In order to verify the superiority of the proposed adaptive algorithm, it is compared with the traditional voting method (MV), the maximum method (MAX), and the mean method (MEAN), shown in Tab.4.

| Different Stage                  | MV     | MAX    | MEAN   | Method of this paper |
|----------------------------------|--------|--------|--------|----------------------|
| initial discharge stage          | 79.7%  | 81.0%  | 83.8%  | 87.8%                |
| discharge development stage      | 80.6%  | 84.7%  | 79.0%  | 88.7%                |
| discharge stabilization stage    | 80.0%  | 85.7%  | 82.9%  | 87.1%                |
| adjacent breakdown stage         | 79.3%  | 84.4%  | 81.0%  | 86.2%                |

It can be seen from the data in the table that the recognition accuracy of the fusion algorithm proposed in this paper is higher than that based on the other three fusion algorithms, reaching more than 85%, and the average discharge recognition rate is about 87.5%, which is compared with the other three algorithms, it is increased by 2%~10%. Through the above experimental data analysis, it is further verified that the proposed algorithm is superior to other general algorithms.

5. Conclusion
Firstly, based on the oil-paper insulation air gap discharge model, 29 characteristic parameters of four discharge patterns are extracted. The K-means method is used to cluster the air gap discharge process into four stages: initial discharge stage, discharge development stage, discharge stability stage and near breakdown stage.

Secondly, comparing the three basic classifiers of SVM, RFC and BPNN, the classifiers are found to have obvious differences in recognition rate, and each has its own superiority. For this reason, three basic classifier classifiers are merged which is very necessary.

Finally, a weighted fusion classifier algorithm is proposed. By introducing credibility as the initial value of the weight, the penalty factor is used to adaptively adjust the weight. Compared with the three traditional fusion algorithms, the algorithm has higher recognition accuracy. A new idea is provided by the method for the identification of the stage of discharge development.

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