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Condition Evaluation and Fault Diagnosis of Power Transformer Based on GAN-CNN

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Abstract: Power transformer is one of the most important components of power system. Maintaining its stable operation is an important guarantee for the normal operation of the power system. In recent years, prognostics and health management (PHM) has been introduced into the health management of power transformers. The key information about its operation is obtained by sensors, which provides a platform for intelligent management. At present, for the fault diagnosis and condition assessment of power transformers, due to the lack of original data feature parameters, the lack of data, and the uneven classification of existing data fault types, it is easy to distort the training model. To overcome the above difficulties, this paper proposes a power transformer condition assessment and fault diagnosis method based on generative adversarial network (GAN) and convolutional neural network (CNN). Through GAN, the original data feature parameters are amplified and generate the artificial data set. The data is trained together through CNN. Finally, the validity and superiority of the proposed method are verified by the measured data and the comparative experiment.

1. Introduction

According to the analysis of national power grid safety operation, power equipment fault is one of the main reasons affecting power grid safety [1], and power transformer as the key pivot equipment of the power grid system, its stable operation is an important basic guarantee for the safe and stable operation of the power system. Effective monitoring and evaluation of power transformer health status, reducing equipment maintenance costs, and ensuring the safety of power transmission and transformation, are of great significance to improve the reliability of the power system [2][3].

In recent years PHM has been introduced into the health management of power transformers[4], using advanced sensor technology, intelligent algorithms, and models to achieve an intelligent and automated system for system monitoring[5][6], prediction, and management. The implementation of PHM can effectively solve the drawbacks of traditional transformer health management methods and provide a platform for the introduction of intelligent transformer tracking and inspection solutions. With PHM technology, information about the transformer's operation can be obtained. Utilizing rational processing and analysis, obtain the operating status of the power transformer, thus enabling condition assessment and fault diagnosis of the transformer [7]. Dissolved Gas Analysis (DGA) is an important component of transformer maintenance based on Condition Based Maintenance (CBM), identifying faults and preventing unplanned transformer shutdowns. The rate of change of these levels can be used to determine the severity of the fault. However, the distribution characteristics of the gas content in the oil are difficult to predict and the mapping between the dissolved gas content or ratio and the type of fault is extremely complex[8]. However, most of the traditional diagnostic methods are limited to threshold diagnosis, and there are problems such as missing codes and over-absolute codes, resulting in low reliability of diagnostic results, which can hardly meet the requirements of power transformer equipment diagnosis in today's power grids. Therefore, in recent years, more and more active detection methods and matching intelligent algorithms have been introduced into the research of power transformer system maintenance. For example, a hierarchical power transformer fault diagnosis model was developed based on SVM[9], but the SVM algorithm itself has difficulties in solving multi-classification problems and is sensitive to the choice of parameters and kernel functions. A plain Bayesian algorithm could be used to calculate the prior probability of training samples and the posterior probability of test samples for fault diagnosis[10], but the plain Bayesian algorithm is not good when the number of attributes is large or the correlation between attributes is large. The neural network model based on different neural network modules in branches of the decision tree is also established as the basic classifier to realize the multi-resolution identification of faults [11], however, it is easy to ignore the correlation between attributes and over-fit.

In summary, there are many methods for assessing and diagnosing the condition of power transformers, but all of them have obvious shortcomings in certain aspects. Therefore, it is of great theoretical significance and engineering value to establish a more comprehensive and accurate prediction model for power transformers based on multiple factors and indicators, taking into account the working condition of transformers under different conditions, and to integrate the advantages of different algorithms to improve the ability of power transformers to prevent and respond to faults, extend transformer life and improve the reliability of power supply to the grid. Given the above shortcomings and considering the small number of original feature parameters of DGA data, the lack of relevant data, and uneven data distribution, this paper uses GAN training to generate artificial data sets, expand the original data to improve the model training effect, and then use CNN to train for fault diagnosis and operational status detection. The validity and superiority of this method are verified by the experiments.

2. Principal Analysis

2.1 Basic Operation State and Fault Defect Analysis of Transformer

2.1.1 Operation Principle of Power Transformer

The power transformer is a kind of static electrical primary equipment that uses insulating oil as an insulating medium and consists of the iron core, coil, voltage regulating switch, oil tank, and so on. It converts one grade of voltage into another grade of voltage with the same frequency through electromagnetic coupling. The power transformer is one of the main components of power system. Transformer is used for power transmission and reception, and the autotransformer is used to couple power systems with different voltage levels. Transformer plays an important role in long-distance power transmission, as shown in Figure 1.

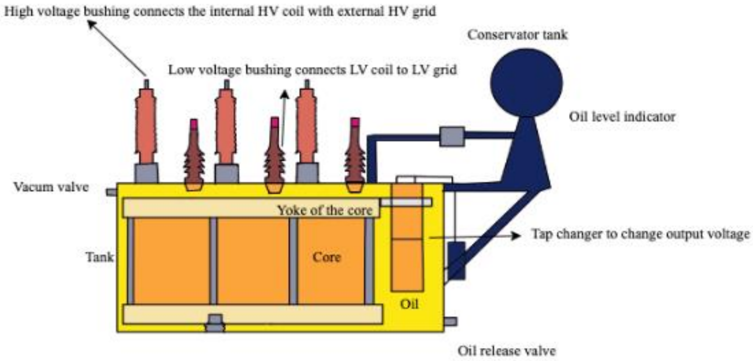

Figure 1 Schematic Diagram of Power Transformer Structure

2.1.2 Characteristics and Typical Detection Methods of Power Transformer Fault

The characteristic quantity of gas in power transformer oil is one of the most important characteristic parameters in the process of fault analysis. DGA has occupied the dominant position of power transformer fault diagnosis in China's power industry since it was formally introduced in China.

Transformer oil is a mixture of many hydrocarbon molecules with different molecular weights. Electrical or thermal faults can break some C-H bonds and C-C bonds, accompanied by the generation of a small number of active hydrogen atoms and unstable free radicals of hydrocarbons. These hydrogen atoms or free radicals are rapidly recombined through complex chemical reactions to form H_2 and low molecular hydrocarbon gases, such as CH_4, C_2H_6, C_2H_4, C_2H_2, etc. and may also generate solid particles of carbon and hydrocarbon polymers. The oxidation of oil also produces a small amount of CO and CO_2, which can accumulate to a significant amount for a long time.

Therefore, different fault types and different fault mechanisms often produce different gases. By detecting the gas composition and content in the oil, the operating state of the power transformer can be largely reflected. DL/T722-2000 "Guidelines for Analysis and Determination of Dissolved Gases in Transformer Oil" summarizes the main characteristic gases and secondary characteristic gases generated by different fault types in Table 1.

Table 1 Fault Type with Gas Component

Fault types	Main gas components	Secondary gas components
Oil overheating	CH4,C2H4	H2,C2H6
Oil and paper overheating	CH4,C2H4,CO,CO2	H2,C2H6
Partial discharge in Oil-Paper Insulation	H2, CH4,CO	CH4,C2H6,CO2
Spark discharge in oil	H2,C2H2	/
Oil arc	H2,C2H2	CH4,CH4,C2H6
Oil and paper arc	H2,C2H2, CO,CO2	CH4,CH4,C2H6

2.2 Construction of fault detection model based on GAN and CNN

2.2.1 Sample Expansion Based on GAN

As a new type of deep generative model, GAN was formally proposed in 2014, and its core idea comes from zero-sum game theory. The main components of GAN include Generator (*G*) and Discriminator (*D*). The main responsibility of the generator is to learn the potential distribution characteristics of real data and synthesize new artificial samples. The main responsibility of the discriminator is to identify real data and generated data and to maximize the accuracy of discrimination. The generator and discriminator continuously improve their generation ability and discrimination ability through confrontation training. The goal of optimization is to achieve the Nash equilibrium point between the two.

To learn the generator's distribution of data x, a priori input noise variable $p_z(z)$ is defined, and then represent the mapping to the data space as $P(z;\ \theta_g)$. Then a second output single scalar multilayer perceptron $D(x;\ \theta_d)$ is defined as:

$$D(x) = \frac{P_{data}(x)}{P_{data}(x) + P_g(x)} \tag{1}$$

In the formula, $D(x)$ denotes the probability that x is from a real sample rather than an artificial sample. We train D to maximize the probability that the training sample is from the generator or the real sample. We also train G to minimize $log(1\text{-}D(G(z)))$, so that G can maximize the generation of artificial samples that D cannot discriminate. In other words, D and G play an adversarial game through the value function $V(G,D)$:

$$\min_G \max_D V(D,G) = E_{x-p_{data}(x)}[\log D(x)] + E_{z-p_z(z)}[\log(1-D(G(z)))] \tag{2}$$

In the training process, the Gaussian distribution noise z is first generated in the noise space. Through the generator, the output vector of the same dimension as the power transformer operating state evaluation sample x is calculated by the multi-layer neural network. The random noise generated in the noise space is mapped to the evaluation feature space through the generator, to obtain a pseudo-sample g. By inputting the real sample x and the artificial sample g into the D at the same time, the discriminator D is trained to judge the probability that the real sample and the artificial sample are real data as much as possible. Usually, this process will go through k times. Secondly, generator G is trained by a multi-layer neural network, which requires that the probability of the generator successfully predicting the real and artificial samples is as low as possible. By this operation, the generator can generate a sample P_g close to the real data distribution P_{data} in an indirect way. Usually, this training process is performed once for k times in step one. By alternating steps 1 and 2 for several rounds, until G and D can not continue to improve, that is $P_{data}=P_g$. Now D cannot distinguish the real sample distribution from the artificial sample distribution, $D(x)=1/2$, which is Nash equilibrium.

2.2.2 Fault Diagnosis and State Analysis Based on CNN

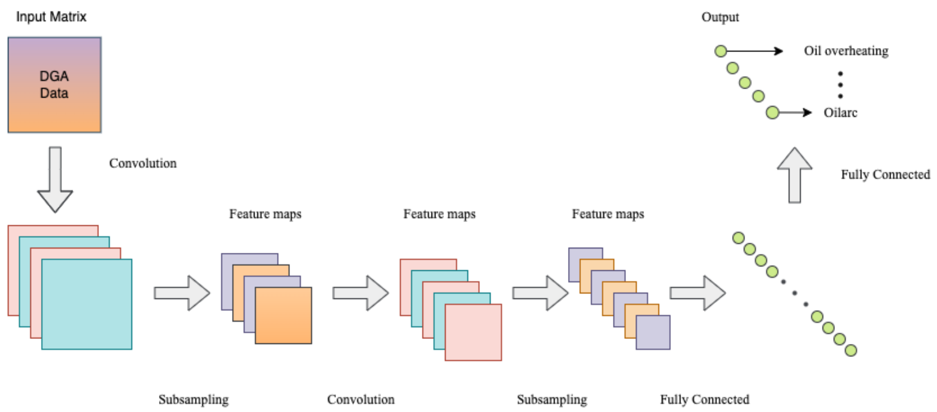

Figure 2 Schematic Diagram of CNN

CNN consists of the input layer, convolution layer, pooling layer, and fully connected layer. Among them, the convolution layer can generate a set of parallel feature maps to extract input features; the pooling layer reduces the amount of data by downsampling, and periodically inserts the pooling layer between the convolutional layers to suppress overfitting; the activation function is used to enhance the nonlinear characteristics of the network, such as sigmoid function and ReLU function. Finally, after several convolutions and maximum pooling layers, the inference process in the neural network is completed by the fully connected layer to identify features, as shown in Figure 2.

The convolution layer aims to extract features by the convolution calculation of the convolution kernel and the input feature map. The convolution process can be defined as:

$$X_j^k = f(\sum_{i \in M_i} X_i^{k-1} - W_{ij}^k + b_j^k) \tag{3}$$

In the formula: X_i^k and X_i^{k-1} represent the output and input characteristic graphs of the k layer network respectively; M_i represents the set of feature maps; W_{ij}^k represents the weight matrix of the convolution kernel; b_j^kdenotes the bias term; $f(\cdot)$ is the activation function. The activation function aims to transform the original linear inseparable multidimensional features into another space and enhance the linear separability of these features. The activation function used in this paper is the ReLu function.

The pooling layer aims to reduce the parameters of the neural network and further compresses the feature map by downsampling. The common pooling methods are average pooling and maximum pooling, which take the average and maximum values in the perceptual domain as the output respectively. This paper adopts the maximum pooling method because observing the maximum value of different features rather than the average value often gives more information. The maximum pooling formula is as follows:

$$P_{ij} = \max_{k \in U_{ij}} a_k \tag{4}$$

Where P_{ij} is the output of the maximum pooling, U_{ij} is the pooling window, and a_k is the element in the pooling window.

3. Model Construction and Result Analysis

3.1 GAN-based Dataset Expansion

3.1.1 Model Establishment

Python is used to import transformer state data, input the adversarial neural network model, train the model, define the size of each batch of training data, the number of training times, and set other relevant hyperparameter settings. The method of simultaneous training of the generator and discriminator is adopted to carry out adversarial training, and finally, Nash equilibrium is reached, and the trained model is saved.

After the GAN model is obtained, the training is generated for the lack of data, and the relevant data is exported. KSComplement and TVComplement are used to evaluate the quality of the attributes and compare the data to complete the evaluation of the model effect.

3.1.2 Parameter Selection

GAN has many hyperparameters that control its learning behavior and may affect the performance of the model, including the quality of the generated data and the computation time.

Epochs and batch size which are the number of iterations performed to optimize their parameters, and the number of samples used in each step. It is set to 300 and 500 respectively. Whether the logarithmic frequency of the classification level used in conditional sampling is set to True. This parameter affects how the model handles the frequency of the classification values used to adjust the remaining values. The size of the random sample passed to the generator is set to 128. The size of the output sample for each residual and the size of the output sample for each discriminator layer are set to (256, 256). The learning rate of the generator and the learning rate of the discriminator are set to 2e-4. The weight attenuation of the generator and discriminator of the Adam optimizer is set to 1e-6.

3.1.3 Model Results and Evaluation

KSComplement is used to calculate the mass fraction of each component gas to evaluate its data quality[13]. Firstly, the numerical distribution is transformed into a Cumulative distribution function and used Kolmogorov-Smirnov statistic to calculate the maximum difference between the two CDFs.

The empirical distribution function F_n for n independent and identically distributed ordered observations X_i is defined as

$$F_n(x) = \frac{1}{n}\sum_{i=1}^{n} 1_{(-\infty,x]}(X_i) \tag{5}$$

To test two one-dimensional probability distributions, the Two-sample Kolmogorov-Smirnov test is adopted. In this case, the Kolmogorov-Smirnov statistic is:

$$D_{n,m} = \sup_x |F_{1,n}(x) - F_{2,m}(x)| \tag{6}$$

For Fault Type categorical variables, we take the TVComplement test[14]. This test computes the Total Variation Distance (TVD) between the real and synthetic columns. To do this, it first computes the frequency of each category value and expresses it as a probability. The TVD statistic compares the differences in probabilities, as shown in the formula below:

$$\delta(R,S) = \frac{1}{2}\sum_{\omega\in\Omega} |R_\omega - S_\omega| \tag{7}$$

Finally, through the analysis and test of each index of the data, the matching degree and quality index of each attribute is shown in Table 2.

Table 1: Components Quality Score and Assessment Methods

Column	Metric	Quality Score
H2	KSComplement	0.584804
CH4	KSComplement	0.888634
C2H6	KSComplement	0.928268
C2H4	KSComplement	0.724497
C2H2	KSComplement	0.881778
Fault Type	TVComplement	0.7347

Next, to further compare the similarity between the original and generated data, an analysis of the orientation between the indicators was carried out. The correlation between the real data and the synthetic data will be compared according to the spearman correlation analysis, as shown in Fig.3.

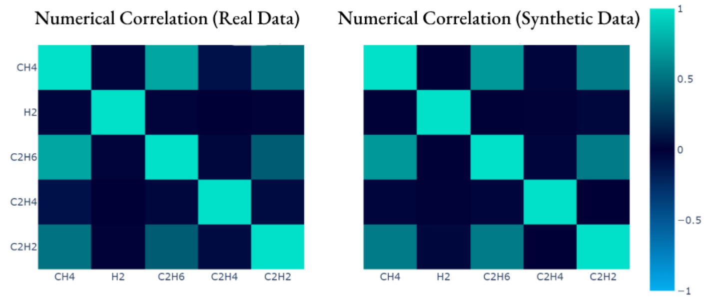

Figure 3 Spearman Correlation Analysis Comparison

Next, we compare the numerical columns with the classification columns by box-plot in Fig.4. By drawing Fault Type and C_2H_6, we can see that the synthetic data matches the correlation between these columns. By drawing the items with higher scores of CH_4 and C_2H_4 in Fig.5, we can see that the comprehensive data are completely consistent with the trend. Through the above analysis, our GAN shows excellent performance in the expansion of the original data set and can improve the overall effect of the model.

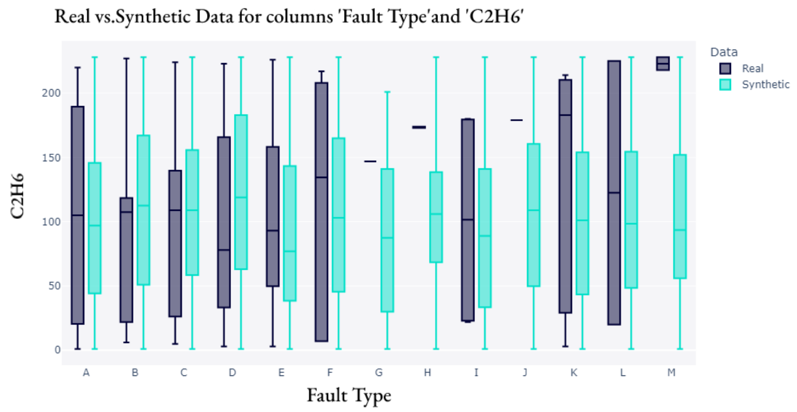

Figure 4 Real vs Synthetic Data distribution box plot

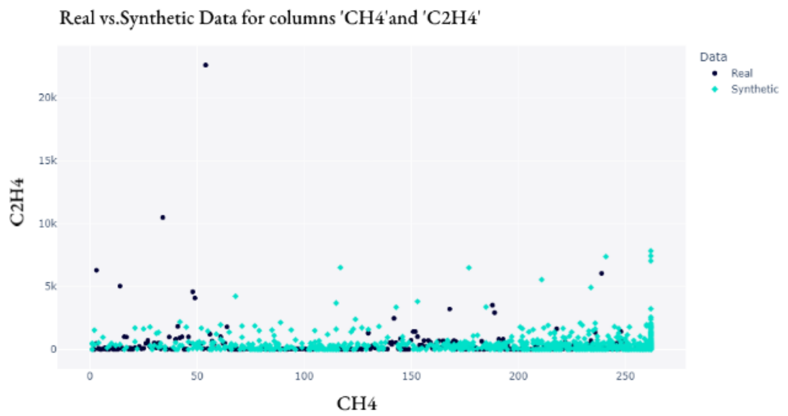

Figure 5 Real vs Synthetic Data distribution scatter diagram

3.2 Fault Detection and State Evaluation Model Based on CNN

3.2.1 Model Establishment

The specific transformer fault diagnosis steps of CNN are as follows: Import the transformer state data, divide the input data into the training set and test set, input the training set into the CNN model according to the batch, and train the model. After the diagnostic model is obtained, the test set is input into it for testing and verification. Because the division of the training set and the test set is random, the use of such data for testing can better reflect the quality of model training, and the test accuracy is obtained through training. Finally, the relevant data is derived, confusion matrix of the contrast CNN is generated to complete the evaluation of the model effect.

3.2.2 Model Training and Implementation

Through CNN, the original data set and the amplified data set are trained for multiple rounds respectively. Through model training, the gas content of each component is used to predict and classify the fault types. Here, some training results of the original data set are selected in Table 3.

Table 2 Partial Failure Prediction Results

Prediction result	Fault Type	H2	C2H4	C2H6	CH4	C2H2
C	C	123	16	178	257	197
D	E	170	430	161	167	103
D	D	25	178	165	172	138
E	E	747	4589	47	48	40
C	C	421	351	124	128	101

3.2.3 Model Effect Comparison

To better compare the training effects of the two, we trained multiple rounds respectively and compared the accuracy. The results are shown in Fig.6. In the final model prediction accuracy, the amplified data set is superior to the original data set in all rounds of prediction.

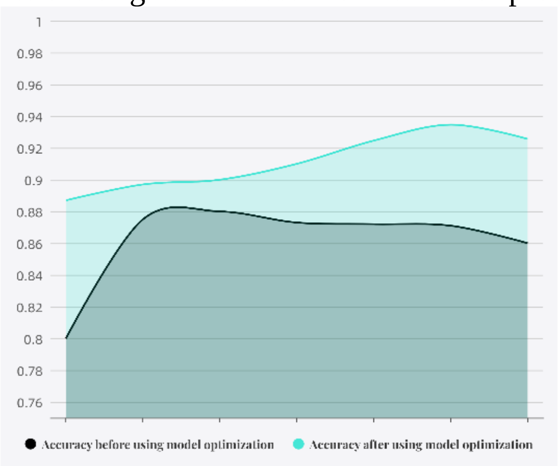

Figure 6 Accuracy Analysis and Comparison Before and After GAN Application

To better demonstrate the diagnostic effect of the model on each fault category, we select the same round of prediction results, and quantitatively analyze the test results of the two model strategies for each category through the confusion matrix, as shown in Fig.7. From the diagram, it can be seen that the model trained using the amplified data set has higher diagnostic accuracy for each category and has a good effect.

From the above analysis, it can be concluded that the CNN model trained using the GAN-amplified data set has obvious advantages in classification and diagnostic accuracy compared with the model generated by the original data.

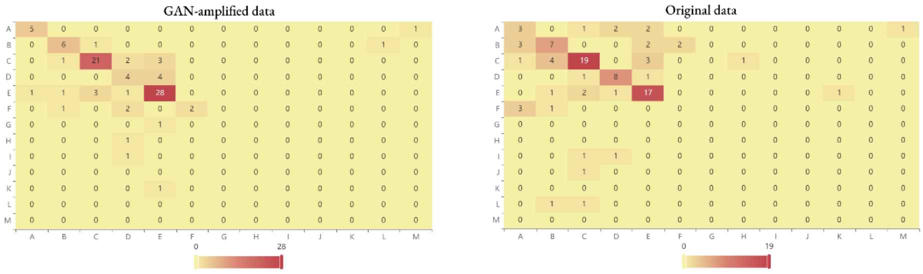

Figure 7 Comparison of Confusion Matrix

4. Conclusion

Aiming at many defects of traditional power transformer fault diagnosis and state evaluation, this paper proposes a research method combining GAN and CNN in deep learning to realize fault diagnosis. Compared with the traditional model, the error rate is too large, the existing data is too dependent, and the uneven distribution of data cannot be effectively processed. The model proposed in this paper can solve the above problems well, and the universality and popularization of the transformer fault diagnosis model are stronger than the traditional model.

The GAN is trained by the existing data, and the amplified data and the original data are input into the CNN to diagnose the actual data of the power transformer in a certain area. It verifies the powerful advantages of the GAN model proposed in this paper in solving the problem of data shortage and imbalance and the good performance of CNN in fault identification.

References

[1] Sun Jianfeng, Ge Rui, Zheng Li, Hu Chaofan. Analysis of the safe operation of the national power grid in 2010[J]. China Electric Power, 2011, 44(05):1-4.

[2] Yin JL. Research on fault diagnosis method of oil-immersed power transformers based on correlation vector machine [D]. North China University of Electric Power, 2013.

[3] Wang Shouxiang, Ge Leijiao, Zhang Qi, Zhuang Jian, Jiang Ling. Analysis of factors influencing distributed energy acceptance capacity of distribution networks[J]. Power supply,2016,33(04):2-7+63.

[4] Xie P. Research on the health management system of oil-immersed power transformers based on data and models[D]. South China University of Technology, 2020.

[5] Jardine A K S, Lin D, Banjevic D . A review on machinery diagnostics and prognostics implementing condition-based maintenance[J]. Mechanical Systems & Signal Processing, 2006, 20(7):1483-1510.

[6] Tsui K L, Chen N, Zhou Q, et al. Prognostics and Health Management: A Review on Data-Driven Approaches[J]. Mathematical Problems in Engineering,2015,(2015-5-19), 2015, 2015(PT.8):1-17.

[7] Xu Jing, Wang Jing, Gao Feng, et al. A review of the research on condition maintenance technology of power equipment[J]. Power Grid Technology, 2000(08): 48-52.

[8] Zhang Han, Liu Weidong, Pan Zhimin, Li Juan. Health condition assessment of transformers based on adaptive probabilistic neural networks[J]. High Voltage Electronics,2022,58(02):103-110.

[9] Dong M, Meng Yy, Xu Changhang, Yan Zhang. A fault diagnosis model for large power transformers based on support vector machine and dissolved gas analysis in oil[J]. Chinese Journal of Electrical Engineering,2003(07):88-92.

[10] Yong Mingchao, Lu Man, Zhou Zhong, Mu Jiqing, Mao Lina. Research on fault diagnosis method of power transformer based on plain Bayesian algorithm[J]. Electrical Applications,2017,36(14):32-35.

[11] Gao W.S., Qian Zheng, Yan Zhang. Fault diagnosis method of power transformer based on decision tree neural network model[J]. Journal of Xi'an Jiaotong University,1999(06):14-19.

[12] Li Kunpeng. Deep learning-based fault diagnosis method for oil-immersed transformers[D]. North China University of Electric Power, 2021.

[13] Sun Jingchao, Kong Maiying, Pal Subhadip (22 June 2021). "The Modified-Half-Normal distribution: Properties and an efficient sampling scheme". Communications in Statistics - Theory and Methods: 1–23. ISSN 0361-0926. S2CID 237919587.

[14] Dimitrova DS, Kaishev VK, Tan S (2020). "Computing the Kolmogorov–Smirnov Distribution when the Underlying cdf is Purely Discrete, Mixed or Continuous". Journal of Statistical Software. 95 (10): 1–42.