Data Augmentation Method for Switchgear Defect Samples Based on Wasserstein Generative Adversarial Network

Xueyou Huang*, Jun Xiong, Yu Zhang, Jingyi Liang, Haoning Zhang and Hui Liu
85 Zhongshan 8th Road, Liwan District, Guangzhou City, Guangdong Province, China
*495357689@qq.com

Abstract. The problem of sample imbalance will lead to poor generalization ability of the deep learning model algorithm, and the phenomenon of overfitting during network training, which limits the accuracy of intelligent fault diagnosis of switchgear equipment. In view of this, this paper proposes a data augmentation method for switchgear defect samples based on Wasserstein generative adversarial network with the partial discharge live detection data of the substation and the real-time switchgear partial discharge simulation experimental data. This method can improve the imbalanced distribution of data, and solve the problems such as the disappearance of gradients and model collapses in the classic generative adversarial network model, and greatly improve the stability of training. Verification through examples and comparison with traditional data augmentation methods. The results show that the data augmentation method mentioned in this paper can more effectively reduce the data imbalance, improve the performance of data-driven technology, and provide data support for subsequent fault diagnosis of switchgear equipment.

1. Introduction
The switchgear is one of the main equipments of the power distribution network, and its operational reliability is closely related to the safety and stability of the power distribution system [1]. With the construction and promotion of smart grids and the wide application of various partial discharge detection technologies, the relevant information of switchgear equipment continues to accumulate. Through the ultra-high frequency detection method, ultrasonic detection method and other detection methods, the data center has accumulated a large amount of data, with typical big data features such as abundant sources and rapid data growth [2-3]. Mining and analyzing the inherent characteristics of the data through data-driven technology, and using machine learning and other methods for fault diagnosis can effectively solve the problems of low accuracy and poor generalization performance caused by relying on expert experience in traditional methods. In recent years, convolutional neural network [4-5], support vector machine [6], BP neural network [7] and other technologies have been widely used in pattern recognition and fault diagnosis of switchgear equipment, and achieved good results.

Since the data-driven technology based on artificial intelligence depends on the quantity and quality of data, a balanced sample category and sufficient quantity are important prerequisites for the strong generalization ability of the model algorithm [8]. However, the failure of switchgear equipment is a small sample event, and the number of time-domain waveform image samples collected is less than that of structured data. The sample data sets of different insulation defect types will be
unbalanced, that is, the number of samples of each type is different, and the number of samples of a certain type is too small, resulting in a large gap. This makes the model prone to overfitting during network training and learning, which limits the accuracy of the recognition effect. Therefore, how to effectively solve the problem of unbalanced sample data and then improve model performance is the focus of current research.

For the problem of unbalanced data learning, the current mainstream solution is to improve the data set to balance the distribution of different categories of the data set, mainly including random undersampling and random oversampling [9]. The random undersampling method improves the distribution of data by randomly discarding the majority of samples in the data set. Although the random undersampling method is simple to operate, randomly discarding samples may result in the loss of some important information and degrade the performance of the model. The random oversampling method is to increase the sample of the minority class in the data set through random copying and other methods to balance the distribution of the data set. But repeatedly copying a few samples will increase the risk of overfitting. In response to this problem, the literature [10] proposed a synthetic minority oversampling technique (SMOTE). This method finds K-nearest neighbor samples for each sample of the minority class, and then inserts in proportion to generate new samples. Although it overcomes the problem of overfitting to a certain extent, there will still be noise and overgeneralization, which makes the model improvement effect limited.

As a generative model for deep learning, generative adversarial networks (GAN) can use unsupervised learning methods to learn input data to estimate the distribution of real data and generate new sample data [11]. At present, the classic GAN model and a large number of improved models based on GAN, such as conditional generative adversarial network (CGAN) [12], Wasserstein generative adversarial network (WGAN) [13] are widely used in computer vision, machine learning and other fields [14-15], and have achieved remarkable success. Based on this, this paper proposes a defect sample enhancement method based on Wasserstein generative countermeasure network to enhance the partial discharge detection data of switchgear equipment. This method uses Wasserstein distance to measure, significantly improves the model collapse, gradient disappearance and other problems of the classic GAN model, and improves the stability of training and the recognition performance of the system. This improves the problem of the small number of particulate defect samples in the partial discharge detection samples, reduces the degree of imbalance, and improves the recognition performance of the intelligent model. Through case analysis and comparative analysis with traditional data enhancement methods, it is shown that the method proposed in this paper can effectively reduce the data imbalance, improve the overall recognition effect, and provide data support for the follow-up partial discharge fault diagnosis and probability prediction of switchgear equipment.

2. Establishment of data set

The data used in this paper comes from the partial discharge live detection of the distribution station and the partial discharge simulation experiment of the real switchgear. A total of four types of partial discharge data samples of switchgear including suspension potential defects, insulation discharge defects, tip corona defects and particle discharge defects were obtained. The types of insulation discharge defects include creeping discharge defects and air gap discharge defects.

Four typical partial discharge defect models were built on the real-type experimental platform. The wiring diagram of the platform is shown in Figure 1. Take the air gap discharge defect model in the insulation discharge as an example. When the model is made, air gaps of different sizes are left in the column epoxy resin and are placed between the flat electrodes. Figure 2 shows the specific model of air gap discharge defects. The power supply used in the experiment is composed of 380V autotransformer, step-up transformer and coupling capacitor, and the maximum output voltage is 150kV. The experiment uses the stepped pressure method to accelerate the cracking process of insulation defects and simulate the severity of different partial discharges.
Figure 1. Partial discharge wiring diagram

Figure 2. Partial discharge mode (air gap discharge defects)

At present, the frequency of on-site inspection of distribution stations is once a month, and regular observations are made on the operation of switchgear equipment. The data collected during the on-site live test have been verified by disassembly, and the actual defects of the equipment are consistent with the data labels. A high-speed oscilloscope and a portable partial discharge detector were used to collect and store UHF time-domain waveform image data under different insulation defects and different discharge quantities. Typical partial discharge signals are shown in Figure 3. 3(a) is suspended discharge. 3(b) is insulation discharge. 3(c) is tip discharge, and 3(d) is particle discharge.

Figure 3. Partial discharge detection data (time-domain waveforms)

3. Model introduction

3.1. GAN model

In 2014, Ian Goodfellow[11] proposed a generative model, GAN, which was inspired by the idea of zero-sum game. The two sides of the GAN game include a generator and a discriminator. The generator usually uses random noise as input and generates sample data; the discriminator takes real data or generated data as input to determine whether the current input is generated data or real data. The generator cannot directly access the real data, and can only learn through the game with the discriminator, usually by implicitly calculating the similarity between the distribution of the candidate model and the distribution corresponding to the actual data[15]. The discriminator can access the synthesized sample and the real sample at the same time, and feedback the error signal to the discriminator by distinguishing the authenticity of the sample. The signal can be used to train the generator to produce better quality counterfeit products, so that the two confront each other and
improve together. The network of generators and discriminators is usually implemented by a multi-layer network consisting of convolutional layers or fully connected layers[16], generating model learning and estimating the statistical distribution of training data. Based on this, it can synthesize new samples from the learned distribution. In this paper, this feature of the generative model is applied to the data augmentation task of the sample.

The training goal of GAN is to obtain the parameters that maximize the classification accuracy of the discriminator and maximize the generator parameters of the cheating discriminator. The optimization process of generator and discriminator can be regarded as a binary minimum problem. First optimize the discriminator to maximize the corresponding function, and then optimize the generator to minimize the corresponding function. The overall objective function can be expressed as:

$$\min_G \max_D V(D,G) = E_{x \sim P(x)}[\log(D(x))] + E_{z \sim P(z)}[\log(1 - D(G(z)))]$$

When optimizing the discriminator, the optimization function is:

$$\max_D V(D,G) = E_{x \sim P(x)}[\log(D(x))] + E_{z \sim P(z)}[\log(1 - D(G(z)))]$$

When optimizing the generator, the optimization function is:

$$\min_G V(D,G) = E_{z \sim P(z)}[\log(1 - D(G(z)))]$$

In the formula: $E$ is the calculation expectation; $P(z)$ is the prior noise; $P(x)$ is the real data distribution; $D(\cdot)$ is the discriminator; $G(\cdot)$ is the generator.

3.2. WGAN model

Although the traditional GAN model can solve the sample imbalance problem to a certain extent, due to its structural characteristics, there are still some problems in the training process[17]. It mainly includes the following two aspects:

- The model collapses. The discriminator and generator training synchronization effects are difficult to grasp and cannot converge at the same time. This will cause the model to collapse, the generator will easily generate samples of repeated categories to avoid the discriminator, and the diversity of samples will be restricted.

- The gradient disappears. Under the optimal condition of the discriminator, the objective function of the generator can be understood as the Jensen-Shannon (JS) divergence between the real sample distribution and the generated sample distribution. When the intersection of the two distributions is negligible, the JS divergence is a fixed constant, which makes the gradient of the generator disappear and cannot be trained.

Therefore, this paper uses an improved GAN model-WGAN, by using the Wasserstein distance instead of the original Jensen-Shannon (JS) divergence, and then evaluate the distance between the real sample and the generated sample. Compared with the traditional method, the advantage of Wasserstein distance is that its calculation is smooth, even if the two distributions do not overlap, they can well reflect the distance between them. And it can use the gradient to update the parameters, but the JS divergence is abrupt and does not have such performance. According to this, the WGAN model has a significant improvement effect on the problems of gradient disappearance and unstable training. The formula for calculating Wasserstein distance is:

$$W(P, P_g) = \inf_{\gamma \in [P, P_g]} E_{(x,y) \sim \gamma} \|x - y\|$$

In the formula: $\gamma\{P, P_g\}$ is the set of joint distribution $\gamma$ composed of real samples $P_r$ and generated samples $P_g$; $E_{(x,y) \sim \gamma} \|x - y\|$ is the expected value of the distance between the generated samples $x$ and the real samples $y$; $W(P, P_g)$ is the lower bound of expectations.

Because it is difficult to calculate the Wasserstein distance, it uses its Kantorovich-Rubinstein dual form[18]:

$$\int_{\mathbb{R}^d} \max_{\|f\|_{Lipschitz} = 1} \mathbb{E}_{x \sim P(x)} f(x) - \mathbb{E}_{z \sim P(z)} f(z) d\gamma$$
\[ W(P_x, P_y) = \frac{1}{k} \sup_{k \geq 1} E_{\mathcal{X} \sim P_x} [f(x)] - E_{\mathcal{Y} \sim P_y} [f(y)] \]  

(5)

The specific algorithm flow is shown in Figure 4. By inputting random noise, the defect data with the smallest number of unbalanced samples is taken as the real sample, and then the defect image is expanded by WGAN to solve the problem of sample imbalance.

4. Results and analysis

This paper is based on the Wasserstein generative adversarial network to expand the samples, and finally the defective samples are expanded to a sample ratio of less than 10. Finally, the sample reaches a relatively balanced state, and the number of various samples is similar, which not only alleviates the sample imbalance, but also prevents over-fitting. The network uses 100-dimensional random data as the data basis of the generator. The hidden layer feature quantity of the generator is 128-512, and the discriminator hidden layer feature quantity is 512-128. Taking a defect sample as an example, the comparison of samples generated by Wasserstein's generative adversarial network is shown in Figure 5. 5(a) is original binary image and 5(b) is its generate sample.

![Figure 5. Comparison of data augmentation with WGAN](image)

Common image expansion methods include image sliding, image cropping, image rotation, optical distortion. The data augmentation method used in this paper is compared with the traditional image augmentation method. Since the detected time-domain wave-form image is a binary image, only rotation and crop-ping are used for expansion. The effect is shown in Figure 6. 6(a) is horizontal flip and 6(b) is sliding crop.

![Figure 6. Images of time-domain waveform based on traditional data augmentation](image)
meaning, so the flipping method cannot be used. Sliding and cropping the samples can enhance the data to a certain extent, that is, choose different steps according to the images of different sample numbers, and then slide and expand the original image to obtain new samples. Using this method can improve the distribution of the number of samples of different defects, but since the actual operation of the switchgear, such as the probability of the occurrence of particle defects is small, the actual detection data volume is much smaller than that of other defect samples. Therefore, relying solely on sliding cropping cannot completely eliminate the imbalance. The method used in this paper can directly input the original image, learn the distribution of the partial discharge pulse waveform, and generate the required samples according to actual needs. A convolutional neural network is used to construct a defect classification model. For the traditional method and the method in this paper, the performance of the defect classification model is compared when the number of expanded samples is different, as shown in Table 1.

| Expansion ratio | Traditional data augmentation /% | Data augmentation of the proposed method /% |
|----------------|---------------------------------|------------------------------------------|
| 1:5            | 89.59                           | 89.65                                    |
| 1:10           | 89.55                           | 89.72                                    |
| 1:20           | 89.46                           | 89.63                                    |

Figure 7 shows the improvement of the model recognition effect compared to the original sample under different sample expansion ratios using different data augmentation methods.

![Figure 7. Comparison of increased performances under different augmentation methods](image)

It can be seen from the figure that the data augmentation method proposed in this paper can reduce the data imbalance, and the recognition effect is more improved than the traditional data augmentation. At the same time, in the case of increasing the expansion ratio, traditional data enhancement has little improvement on the performance of the model, or even a decline. It can be judged that the expansion sample is similar to the original data, and overfitting has occurred. The method used in this paper increases the model recognition rate while the expansion ratio increases, but it still maintains the improvement of the overall recognition rate, which can illustrate the effectiveness and robustness of the method. In practical engineering applications, first determine whether the unbalance rate of the sample exceeds the set threshold. If it exceeds, you can use data augmentation methods to expand the sample for different data situations to improve the performance of the diagnostic system.

5. Conclusion
Aiming at the problem of sample imbalance in the intelligent diagnosis of switchgear, this paper proposes an augmentation method of defect samples based on Wasserstein generative adversarial network. Verification through examples and comparison with other traditional enhancement methods verify the effectiveness and robustness of the method. This method can also be used for other types of
unbalanced sample sets, and the data can be enhanced according to actual needs to improve model performance and lay the foundation for subsequent fault diagnosis.

Acknowledgments
This work is supported by Science and Technology Project of China Southern Power Grid Company (Research and Application of Key Techniques for Standardization and Efficient Processing of Distribution Equipment Condition Detection Data, No.082100KK52190004).

References
[1] WANG Changchang, LI Fuqi, GAO Shengyou. Online monitoring and fault diagnosis of power equipment[M]. Beijing: Tsinghua University Press, 2006.
[2] ZHANG Jiayu. Discussion on partial discharge detection technology and development prospect of switch cabinet[J]. Technology Innovation and Application, 2020(11): 146-147.
[3] LI Zhiyong, ZHOU Hua. Application of Partial Discharge Live Detection Technology for High Voltage Switchgear[J]. Telecom Power Technology, 2020, 37(03): 133-134.
[4] HUANG Xueyou, ZHANG Yu, MA Shuheng, et al. Fault Rate Prediction Method of Switchgear Based on Convolutional Neural Network[J]. Electric Engineering, 2020(05): 21-24.
[5] WANG Feifei, RUAN Aimin, WEI Gang, et al. Partial discharge fault identification of switchgear based on convolutional neural network[J]. Electrical Engineering, 2019, 20(04): 76-81.
[6] WANG huidong, CHEN Feng. Signal Recognition of Switching Cabinet based on EMD Decomposition and GWO-SVM[J]. Automation Panorama, 2019(12): 120-124.
[7] GUO Wenqiang, DONG Yao, LI Qinghua. Application of PSO-BP neural network in temperature prediction for switchgear equipment[J]. Journal of Shanxi University of Science & Technology, 2020, 38(01): 149-153.
[8] HUANG Jianming, LI Xiaoming, QU Hezuo, et al. Method for fault type identification of transmission line considering waveform signal information and unbalanced dataset[J]. Proceedings of the CSEE, 2017, 37(11): 3099-3107 (in Chinese).
[9] FENG Hongwei, YAO Bo, GAO Yuan, et al. Imbalanced data processing algorithm based on boundary mixed sampling[J]. Control and Decision, 2017, 32(10): 1831-1836.
[10] Chawla N V, Bowyer K W, Hall L O, et al. SMOTE: synthetic minority over-sampling technique [J]. Journal of Artificial Intelligence Research, 2002(16): 321-357.
[11] Goodfellow I, Pouget-Abadie J, Mirza M, et al. Generative adversarial nets[C]//Conference on Neural Information Processing Systems, Montreal, Canada, 2014:2672-2680.
[12] Mirza M, Osindero S. Conditional generative adversarial nets[J]. arXiv:1411.1784, 2014.
[13] Arjovsky M, Chintala S, Bottou L. Wasserstein GAN[J]. arXiv:1701.07875, 2017.
[14] WU Shaoqian, LI Ximing. Survey on Research Progress of Generating Adversarial Networks[J]. Journal of Frontiers of Computer Science and Technology, 2020, 14(03): 377-388.
[15] LUO Jia, HUANG Jinying. Generative adversarial network: An overview[J]. Chinese Journal of Scientific Instrument, 2019, 40(03): 74-84.
[16] XIE Xiaobo. Research on Classification of Imbalanced Dataset Based on Generative Adversarial Networks[D]. Nanjing University of Posts and Telecommunications, 2019.
[17] Hong Y, Hwang U, Yoo J, et al. How Generative Adversarial Networks and Their Variants Work: An Overview[J]. ACM Computing Surveys (CSUR), 2019, 52(1): 10.
[18] WANG Shouxiang, CHEN Haiwen, PAN Zhixin, et al. A Reconstruction Method for Missing Data in Power System Measurement Using an Improved Generative Adversarial Network[J]. Proceedings of the CSEE, 2019, 39(01): 56-64+320.