Fault Diagnosis of Distribution Terminal Units’ Measurement System Based on Generative Adversarial Network Combined with Convolutional Neural Network

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Abstract. As the condition monitoring and control device in the distribution automation system, the abnormal or fault state of distribution terminal units’ measurement system will negatively affect the quality of measured electrical quantities, and therefore, the fast and accurate discrimination of the abnormal state’s data will improve the reliability of distribution automation system. This paper proposes a method, which is based on generative adversarial network (GAN) combined with convolutional neural network (CNN), to discriminate the specific fault category of distribution terminals’ measuring electrical data. Firstly, four fault state characteristic time-frequency domain graph models of terminals’ AC voltage sampling data are established, which based on Fourier transform (STFT). Then, take advantage of GAN’s reconstruction of input graph data, to generate additional time-frequency sample graphs expanding the sample size of training set, which will be used to train a CNN to diagnosis and classify the fault state of terminals from measuring data. Finally, three training sets with different capacity expansion modes are set up to compare and verify that the method of GAN combined with CNN proposed in this paper improves the discrimination accuracy on the fault data, and the validation of diagnosis terminals’ measurement system.

1. Introduction

The distribution terminal units, which usually installed in the medium voltage substation, are the important condition monitoring and control equipment in distribution automation system [1-3]. Affected by the installation environment, different product quality and performance factors, the terminals’ measurement system frequently dysfunction or abnormally operate, for these relative problems, however, lacking online fault diagnosis and discriminant methods make the negative effect of terminals’ fault much worse [3]. Therefore, it is necessary to study a method to fully exploit the information potential contained in the measured electrical data of terminals, and to diagnosis measurement system’s fault by judging whether the electrical monitoring data state of the distribution terminal are normal, so as to improve the reliability of the terminals.
As for the research on discrimination method of electrical equipment’s abnormal feature data, literature [4] established the BP neural network to complete identification fault type based on some typical faults sampled data of voltage transformer, however, the identification accuracy and generalization performance of the method still have great room to improvement. Literature [5] used Elman neural network’s strong adaptability to diagnose the fault of high-voltage measurement system, but the capacity of analysis feature samples was not enough, which might affect the results of fault diagnosis and discrimination. Literature [6-7] respectively used the method of Wavelet Transformation to extract feature of fault and comparison of transverse and longitudinal current to identify the fault of the transformer. However, the selection of fault features was subjective and incomplete to a certain extent. Literature [8] deeply analysed mechanism and equivalent model of harmonic type fault for transformer, but did not conduct any in-depth research on discrimination based on data analysis.

For the research on deep learning methods in the aspects of learning data feature and identification of data pattern, literature [9] realized the accurate classification of time-frequency diagrams of different bearing vibration faults through deep CNN. Literature [10] studied Wavelet Transform method to generate wavelet map for the vibration signals of loose transformer windings and loose iron cores, and generate grey-scale feature graph, which were used to train CNN, and then successfully realized identification of the vibration signals the deep net. The above studies are all based on CNN and have achieved good results in various pattern recognition and classification problems. However, the sample size of training required by the CNN is large, and the over-fitting problem of the model on the small-scale training sample has not been solved yet. For the enhancement and repair of feature data, literature [11] trained GAN to learn the ability of generating new face pictures, which improved its great benefit on data refactoring and enhancement.

This paper proposes a deep learning method based on GAN combined with CNN, aiming to accurate discrimination abnormal voltage measured by distribution terminals’ measurement system. Firstly, four fault state characteristic time-frequency domain graph models of terminals’ AC voltage sampling data are established, which based on STFT. Then, take advantage of GAN’s reconstruction of input graph data, to generate additional time-frequency sample graphs expanding the sample size of training set, which will be used to train a CNN to diagnosis and classify the fault state of terminals from measuring data. Finally, three training sets with different capacity expansion modes are set up to compare and verify that the method of GAN combined with CNN proposed in this paper improves the discrimination accuracy on the fault data, and the validation of diagnosis terminals’ measurement system.

2. Fault feature model of voltage data
According to the characteristics of ac voltage between the normal and abnormal state of the distribution terminals’ voltage measurement and acquisition system, the four feature data models are respectively established, as the object of data discrimination and fault diagnosis.

2.1. Measurement data model of normal state
Due to the interference from environment, the distribution terminals’ measured voltage data might contain a certain amount of random noise in actual operation. Generally, it can be considered that the noise part of data is subject to Gaussian distribution. The normal state data model considering the error of acquisition and measurement is shown in the following equation:

\[ f(t) = A\sin(\omega t + \varphi) + N(0,\delta^2) \]  

(1)

Where, \( N(0,\delta^2) \) is the measurement noise of Gaussian distribution with mean of zero and variance of \( \delta^2 \), in turn, \( A \), \( \omega \) and \( \varphi \) are the amplitude, angular frequency and phase angle of the measured voltage data.

2.2. Measurement data model of accuracy distortion
When the fault occurs in the signal processing module such as the transformer and signal transmission unit in the distribution terminals’ measurement system, the accuracy of the measured signals will be distorted, and the noise part may have the feature of marked change. In the case of precision distortion fault, the average value of voltage measurements remains unchanged and the measurement variance changes, expressed as $N_f(0, \sigma_f^2)$. The fault data model at this time is shown in the following equation:

$$f(t) = A \sin(\omega t + \varphi) + N(0, \sigma^2) + N_f(0, \sigma_f^2)$$

(2)

2.3. Measurement data model of decaying oscillation

When the measurement device in the distribution terminals is aging or decaying, the measured data usually have a certain characteristic of oscillation attenuation. The fault data model at this time is shown in the following equation:

$$f(t) = e^{-bt} \cdot A \sin(\omega t + \varphi) + N(0, \sigma^2)$$

(3)

Where, $e^{-bt}$ is exponential attenuation coefficient; $b$ is a real number greater than 0, which expressing the magnitude of exponential decay; $N(0, \sigma^2)$ is the Gaussian noise term of such measurement data, indicating the measurement error.

2.4. Measurement data model with harmonics

The measurement element in the distribution terminal may deviate from the fundamental frequency due to environmental interference or component fault. For example, electromagnetic transformer will occur when the excitation characteristic of electromagnetic transformer is degraded, resulting in the measurement containing high-order harmonic components [8]. The fault data model at this time is shown in the following equation:

$$f(t) = A \sin(\omega t + \varphi) + A_2 \sin[2\omega t + \varphi_2] + A_3 \sin[3\omega t + \varphi_3] + \ldots + N(0, \sigma^2)$$

(4)

2.5. Time-frequency graph of the measurement data model

![Figure 1. Time-frequency graph of normal-state data.](image1)

![Figure 2. Time-frequency graph of accuracy distortion data.](image2)
The data models of the distribution terminal established above belong to time-domain. In order to strengthen the classification characteristics of different data models, STFT is introduced to convert the digital data samples into time-frequency graph containing time-domain and frequency-domain feature information.

Based on the result of the STFT, the measurement data of different time-frequency graphs, as shown in figure 1-4, horizontal axis represents time sampling data and the vertical axis represents the different frequency components, and the depth of the graph’s pixel colour represents the amplitude of different frequency component at the same time. Generally, the four different type time-frequency graphs are evidently different in the graphics characteristics such as shape, colour, therefore, it can be feed into CNN, converting the recognition of time-domain data to discrimination the feature pictures.

3. Discrimination of feature graph based on GAN combined with CNN

In order to give full play to GAN's ability of feature learning and data regeneration and CNN's huge advantages in image recognition. The identification and classification of fault feature data model, which based on GAN combined with CNN, comprehensively established in this paper is shown in figure 5. STFT is used to convert the AC voltage sample data into time-frequency feature graph samples, and the training set composed of time-frequency graphs of various types of faults feed into GAN to generate reconstructed time-frequency graphs, so as to expand capacity of four types of faults’ training sets. Then, the expanded training sets are used to train CNN, so as to realize the classification and identification of four types fault feature data.
3.1. Capacity expansion model of time-frequency graph based on GAN

GAN (Generative Adversarial Network) is a kind of probability generation model, which consists of the Generator G (Generator) and Discriminant D (Discriminator). It could learn the distribution of the original data through confrontation training.

The purpose of trained G is to imitate and master the distribution of sample data, making the performance of distribution $G(z)$ on D, which expressed as $D(G(z))$, as consistent as possible with the performance of real data $x$ on D, which expressed as $D(x)$, so that D cannot distinguish the generated samples from real samples. The purpose of trained D is to correctly distinguish fake samples from generated samples. The above logical relationship can be expressed as maximum-minimum problem [11], and its mathematical expression is as follows:

$$\min_{G} \max_{D} E_{x \sim p_{x}} \log(D(x)) + E_{z \sim p_{z}} [\log(1 - D(z))]$$  \hspace{1cm} (5)

Where, $x$ is characteristic sequence and $z$ is random number sequence; $p_{x}$ represents the time-frequency feature graphs of the original true data; $p_{z}$ represents the time-frequency feature graphs of new fake data generated by G.

D and G, through continuous cross optimization, improve their respective discrimination and generation ability respectively. This optimization process is to find the Nash equilibrium of the game process between them. When the training stops, the discriminator D could hardly distinguish the difference between the time-frequency graphs of distribution terminals’ fault feature data, which generated by the generator, and the time-frequency diagram of the original data.

In order to facilitate the processing of time-frequency graphs of image types, deep convolutional generative adversarial networks (DC-GAN) are used in this paper, which is composed of two mirrored convolutional neural networks. In addition to the output layer of G and the input layer of D, batch normalization is added to all other layers, which will help stabilize the optimization process of objective function gradient to some extent.
3.2. Time-frequency graph recognition model based on CNN

Convolutional Neural Network (CNN) is a multilayer perceptron designed to identify two-dimensional feature graphs. It is a deep network model with multiple hidden layers, which can transform low-level features into high-level features through feature transmission layer by layer, so as to realize feature learning and expression. Compared with BP neural network and other shallow networks, CNN has a stronger ability to learn and express complex features, and a faster operation speed, and could avoid the problem of getting into the local extreme.

The time-frequency graphs of various data samples are fed into CNN, and then after process of pre-processing and normalization, the input graphs are successively processed through convolution layer, pooling layer and the full connection layer, and the feature extraction and dimensionality reduction of data are completed through activation function, and finally output the type number of fault feature data, which express the identification and classification of fault feature data.

As for the convolution layer of CNN, different convolution kernels are used to convolve with the feature graph, and the feature graph after dimensionality reduction is obtained by activating the function. The convolution process could be expressed as follows:

\[ x'_j = f(\sum_{i=M}^{l} x'^{l+1}_i * k^{l+1}_j + b^l_j) \]  

(6)

Where: \( x'_j \) represents the output \( j \) of the layer \( l \); \( k^l_j \) represents a convolution kernel of the convolution layer; \( * \) represents the convolution operation; \( b^l_j \) represents the bias of the convolutional layer; \( f(\cdot) \) is an activation function, and the ReLU function is commonly used one, which could expressed as follows:

\[ f(x) = \begin{cases} 
  x & x > 0 \\
  0 & x \leq 0 
\end{cases} \]  

(7)

In the pooling layer, the maximum value (maximum pooling) or average value (average pooling) of the feature graph output for the convolution layer in each non-overlapping region of size \( n \times n \) is selected, so as to further reduce the dimension of the feature graph.

In the full connection layer, input all the one-dimensional feature vectors expanded by the feature graph of the previous layer, and output the final classification after weighted and imported into the activation function. In this paper, the Softmax function is used as the activation function of output layer.

Based on the classification task implemented by CNN, the common loss functions include mean square error function, cross entropy function and negative logarithmic likelihood function. The cross entropy function which has good performance is selected in this paper, and the expression is as follows:

\[ \text{loss} = -\frac{1}{n} \sum_{i=1}^{n} [y_i \ln \hat{y}_i + (1 - y_i) \ln(1 - \hat{y}_i)] \]  

(8)

Where, \( n \) is the number of fault feature samples; \( y \) is the true value; \( \hat{y} \) is the predicted value.

4. Example

4.1. Power distribution terminal ac sampling data sample generation

By the function (1) - (4) representing the distribution of terminals’ fault voltage feature sampling data samples, which were generated and simulated in Matlab, the set for sampling frequency of AC voltage is 250 HZ, and sampled four cycles of power frequency measurement data points (20 voltage measurement points) composed as one data sample. Adjust the parameters of each data model for simulation, as seen in table 1 for specific simulation parameters and sample size.
Table 1. Simulation parameter setting table of voltage model

| Type                        | Parameter                                                                 | The number of samples |
|-----------------------------|---------------------------------------------------------------------------|-----------------------|
| Normal                      | $\phi \in U[0,2\pi]$                                                     | 300                   |
|                             | $\delta \in U[0,0.1]$                                                   |                       |
|                             | $\phi \in U[0,2\pi]$                                                     |                       |
| Accuracy distortion         | $\delta \in U[0,0.1]$                                                   | 300                   |
|                             | $\delta \in U[0,0.1]$                                                   |                       |
| Damped oscillation          | $b \in U[5,20]$                                                         | 300                   |
|                             | $\delta \in U[0,0.1]$                                                   |                       |
|                             | $\phi \in U[0,2\pi]$                                                     |                       |
| Harmonic interference       | $A_x \in U[0, A]$                                                       | 300                   |
|                             | $\phi \in U[0,2\pi]$                                                     |                       |

Operating Matlab, use spectrogram function, which is a short-term Fourier analysis function, to convert the simulated sampled voltage data into time-frequency graph samples.

4.2. Combined neural network structure and fault identification results analysis

Table 2. Structure parameters table of DCGAN

| Component | Structure | Dimension of input [height, width, depth] | Dimension of output [height, width, depth] |
|-----------|-----------|-------------------------------------------|-------------------------------------------|
| D         | Con Layer1 | [64,64,3] | [32,32,64] |
|           | Con Layer2 | [32,32,64] | [16,16,128] |
|           | Con Layer3 | [16,16,128] | [8,8,256] |
|           | Con Layer4 | [8,8,256] | [4,4,512] |
|           | Full-connected Layer5 | [1024] | [1] |
|           | Full-connected Layer6 | [100] | [4,4,1024] |
|           | De-con Layer7 | [4,4,1024] | [8,8,12] |
| G         | De-con Layer8 | [8,8,512] | [16,16,256] |
|           | De-con Layer9 | [16,16,256] | [32,32,128] |
|           | De-con Layer10 | [32,32,128] | [64,64,3] |

Table 3. Structure parameters table of CNN

| Structure   | Dimension of input [height, width] | Numbers of kernels (or output dimension) | Dimension of Kernel [height, width] |
|-------------|------------------------------------|-----------------------------------------|------------------------------------|
| Con Layer1  | [64,64]                            | 16                                      | [3,3]                              |
| Pooling Layer2 | [32,32,64]                    | 16                                      | [3,3]                              |
| Con Layer3  | [16,16,128]                        | 32                                      | [3,3]                              |
| Pooling Layer4 | [8,8,256]                    | 64                                      | [3,3]                              |
| Full-connected Layer5 | [1024]                    | [1024]                                  | [3,3]                              |
| Full-connected Layer6 | [100]                     | [4]                                     | [3,3]                              |
Based on Tensorflow, which is the deep learning framework of Google, the processing of data time-frequency graph clipping and data standardization is carried out. After that, the network architectures of GAN and CNN were built and corresponding model parameters were set, and corresponding parameters are shown in table 2 and table 3.

This paper specifically selected LeNet-5 as CNN network structure, and Adam algorithm is adopted to optimize the loss function. The global learning rate is set to 0.0001, and each batch is 20 samples.

Against the new time-frequency graphs of all kinds of data samples generated by generator G in neural network, take normal data and attenuated oscillation data as examples. After training GAN with different periods, new time-frequency graph samples of data are generated, as shown in figure 6. With the increase of training step length, the time-frequency graph generated by GAN is closer to the real training sample, that is, the more features of simulation data samples are learned, so that the random sequence can generate new time-frequency graph data samples after passing through multiple trained de-convolution layers, so as to expand the sample size of the training set.

![Figure 6. Time-frequency graph of normal samples generated based on GAN.](image)

GAN (step=50) after training the training set generates 100 new time-frequency graphs of data samples of various types to expand the capacity of training set input into CNN network. Four hundred time-frequency graphs were randomly selected from the simulation-generated data sample set as the test set of CNN fault classifier. Three different CNN training sets are set to compare the classification performance results of the methods used in this paper:

1) Training set A: all kinds of real data samples generated by the original simulation (without GAN expansion) are composed of $4 \times 200 = 800$ time-frequency characteristic graph.
2) Training set B: the mixed training set generated by GAN after expansion is composed of time-frequency characteristic graph of $4 \times (200 + 100) = 1200$, which contains both real data samples and new data samples generated by GAN.

3) Training set C: in the real data sample set generated by the original simulation (the capacity is 800), 400 time-frequency graphs samples are randomly copied to form the expanded training set, which is composed of $4 \times (200 + 100) = 1200$ time-frequency graphs. The expansion mode is only random replication on the original sample set, and actually no data samples with new characteristics are added. The purpose of setting the training set is to eliminate the influence of the training set capacity on the CNN fault classifier so as to better compare the performance results of the method used in this paper.

Different training sets were input into the CNN network, and the loss function values on the training set with different training steps were counted and compared with the test accuracy on the test set. The results were shown in figure 7 and figure 8 respectively.

![Figure 7. Loss value diagram of CNN training process.](image1)

![Figure 8. The recognition accuracy graph of CNN on test set.](image2)

5. Conclusion
This paper presents a fault diagnosis method of voltage sampling module of distribution terminals with GAN and CNN. Firstly, this paper established normal state voltage sampling data model containing noise part and three types of approximate mathematical model of abnormal state data, then through STFT converting simulation data into a comprehensive time-frequency graphs, and the generated data samples by 2:1 is divided into the original training set and testing set. On the basis of GAN, feature learning, pattern generation and expansion were carried out for the original training set of various types of data samples. Then, the expanded samples were used to train the CNN (lenet-5) model, and the performance results of fault classification on the same test set were obtained through three training sets with different capacities and expansion modes. The simulation data examples and the training verification results of combined neural network showed that:

1) The time-frequency graphs obtained by STFT could be much easier to distinguish the sampling data of distribution terminals with different fault types.

2) After GAN generated new data samples, the training sets B had a good classification result on the testing sets, indicating that GAN could learn and regenerate the features of limited data samples and realize the expansion of a limited number of sample data.

3) In the training process of CNN with the simulation data of time-frequency graph containing noise, the input values of CNN loss function of different capacity and different expansion mode training sets have little difference, and they all have a good decline process. The fault classification model based on CNN would have a good difference effect on various types of fault data.

4) The accuracy of training sets with different capacities and expansion modes is different on the same test set. Compared with the original training data set without expansion and the expansion data set after simple random replication, the accuracy of identification of the expansion training set
generated by GAN is significantly improved on the test set. It is proved that GAN combined with CNN can improve the generalization performance of fault time-frequency graph recognition model, namely, the recognition accuracy on unknown data. However, the specific mathematical relationship between GAN expansion capacity and the improvement of recognition accuracy on the CNN test set and the possible upper limit have not been proved in this paper, and further studies are still needed.

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