Fault diagnosis of power capacitors using a convolutional neural network combined with the chaotic synchronisation method and the empirical mode decomposition method

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Abstract
This study combined a Convolutional Neural Network (CNN) with the chaos theory and the Empirical Mode Decomposition (EMD) method for the attenuation fault recognition of power capacitors. First, it built six capacitor analysis models, including normal capacitors, failed capacitors, and normal capacitors attenuated by 20–80%. Then a power testing machine was used for an applied voltage test of the capacitor. The EMD method was combined with the chaos synchronisation detection method to chart the discharge signals of the voltage and current that was captured by a high frequency oscilloscope into a 3D chaotic error scatter plot, as the fault diagnosis feature image. Finally, the CNN algorithm was used for the capacitor fault detection. The advantages of the proposed method are that big data are compressed to extract meaningful feature images, the operating state of the power capacitor can be detected effectively, and faults can be diagnosed according to the electrical signal change of the power capacitor. The actual measurement results showed that the accuracy of the proposed method was as high as 97% and has a high efficiency of noise rejection ability, which indicates that the method could be applied to other power-related fields in the future.

1 | INTRODUCTION

With both the technological and economic developments in recent years, the quality of people's lives has improved continuously, and this has led to higher requirements for the stable and safe operation of power systems. One of the important pieces of equipment in a power system is the power capacitor. High temperatures, voltages, and loads can cause efficiency decays and even failure over time, thus indirectly inducing equipment faults or power outages. If problems can be diagnosed before the power capacitor fails and if replacements and repairs can be implemented, the safety and stability of the equipment could be greatly enhanced, and the hazards and losses induced by power outage could be reduced [1]

At present, conventional periodic planned testing is usually applied to protect power capacitor equipment [2], and related documents have studied the faults in power capacitors. Wu et al. [3] used aging tests to obtain capacitor voltage signal data, and they discussed the effects of partial discharge, space charge, and the thermal effect on the insulation failure of capacitors. They found that, when insulation defects occurred inside the capacitor, the electric field was relatively concentrated, which induced a partial discharge. As the thermal effect accelerates the material aging process, the space charge is a direct factor that induces the capacitor breakdown. Liang et al. [4] constructed a two-dimensional numerical model of internal electric field for the structure of a power capacitor, they simulated the electric field distribution and dielectric breakdown characteristics of power capacitors, they discussed the relationship between the edge electric field distribution voltage and dielectric breakdown strength, and they provided a theoretical basis for the design and operation of a power capacitor. Liang et al. [5] used the 3D finite volume method in a computation model for the internal temperature of power capacitors, they analysed the temperature distribution characteristic at the hottest spot of the power capacitor, which found that the power capacitor working temperature rose...
due to the heating of the power capacitor which was induced by the internal dielectric loss, and they validated the direct effect of the working temperature on the service life of power capacitors, according to the data simulation and test results. Wang et al. [6] developed a capacitor temperature measurement system for a fibre Bragg grating temperature sensor, they used Fluent software to analyse the power capacitor temperature distribution characteristic, and accurately measured the internal and external temperatures of the power capacitor, which solved the difficulty of measuring the internal temperature of a power capacitor, and this method can be used for the on-line monitoring of the operating temperature of power capacitors. Guillermin et al. [7] proposed a model for describing the dielectric failure and degeneration of power capacitors, and performed numerous breakdown tests to monitor the electrical defect and gas defect characteristics, and the results indicated that the internal dielectric defect was closely related to the degeneration characteristics. Thus, using the model could help to predict the state of a power capacitor that is reaching the end of its service life. Wang et al. [8] proposed the extension theory for fault diagnosis of normal and aging 220 V low-voltage capacitors and to detect feature signals with chaotic eye coordinates, which can enabled 84% accuracy of the recognition results. However, when the extension theory is used to build the fault detection model of capacitors, the ranges of the classical domain and node domain of the matter-element model of the capacitors must be set in advance based on experts’ experience, which increases the complexity of the algorithm during pre-work. However, while present studies emphasize the causes of the faults in power capacitors, few studies have effectively tested the abnormal state during the operational process of power capacitor equipment; thus, the potential faults in power capacitor equipment cannot be detected in a timely manner, and the running stability and safety of power systems are influenced. Therefore, the main objective of this study is to develop a practical test method for power capacitors in power systems, where the features of electrical signals are extracted and identified by algorithms, and the attenuation degree inside the capacitors is analysed to effectively judge the fault type, in order to increase the line power factor and to protect the power quality [9, 10].

The proposed method uses the measured system line voltage and line current as the main signals. The 3D chaotic error scatter plot formed from the main feature data is used as the feature image for fault detection by using Empirical Mode Decomposition (EMD) and the chaos synchronisation detection system. The Convolutional Neural Network (CNN) is then used for learning and recognition, so as to recognize the power capacitor fault type by using the image features. The proposed fault diagnosis algorithms are divided into the following three main classes:

The EMD method is characterized by providing a time-frequency analysis method of self-adaptive decomposition for unsteady state nonlinear signals to decompose complex data signals into some finite and Intrinsic Mode Functions (IMF) [11–13], which are then used to extract a few representative feature signals from the numerous fault signals of power capacitors. The feature signals decomposed by EMD are highly sensitive to the input and output signals of chaotic synchronisation detection, and even if the input signal changes slightly, the final output result will still have an apparent scale effect [14–16]. The fault feature signals are then drawn into a feature chaotic scatter diagram. Finally, the feature chaotic scatter diagram has the ability to extract automatic features through the convolutional neural network, which is extensively used in image classification research [17–20], where the fault type is directly identified by using the feature images. The findings show that there are six fault types of power capacitors, 30 signal data were collected from each type, 180 data were used as the CNN training signal data, and after 123 iterations of learning, the training accuracy that was achieved was 100%. Moreover, 60 new signal data that were different from the training data were collected for validation, and the network recognition accuracy rate was also 97%.

2 | POWER CAPACITOR INSPECTION TEST METHOD

Faults of capacitors are caused by potential internal defects, poor wiring during installation, or forced damage or overload that accelerate their deterioration and reduce their electric insulation strength. This study performed an AC voltage withstand test for a power capacitor [21, 22]. In the test, an autotransformer regulated the voltage for the power capacitor, so as to measure the partial discharge phenomenon in a low-voltage state.

First, the defects in the test power capacitor were pre-treated, and then the power testing machine performed a continuous boost discharge test of the capacitor. A High Frequency Current Transformer (HFCT) and high frequency oscilloscope were used to capture the current signal of the partial discharge. Next, the signature waveform of the discharge signal was obtained by using the empirical mode decomposition method, combined with the chaos synchronisation detection method. The 3D chaotic error scatter plot of the discharge signal was used as the feature image for the fault diagnosis. Finally, the CNN algorithm was used for the fault recognition of the power capacitor. Figure 1 illustrates the overall power capacitor fault diagnosis process. The power capacitor discharge detection testing platform is shown in Figure 2. The overall experimental process was comprised of the power capacitor defect construction and a self-made detection circuit design (high-pass filter and non-inverting amplifier), as described below.

2.1 | Power capacitor defect construction

This study utilized 70 disused 440 V/50 kvar low-voltage phase advance power capacitors (Shihlin Electric & Engineering), and measured the condition of each capacitor by an LCR impedance analyser. Such capacitors are mainly used in actual power distribution systems, including substations, industrial plants, and transmission lines, as reactive power needed to supply loads for power factor improvement purposes. It is expected that long-term operation will lead to varying degrees of attenuation
inside the capacitors. There are six types of capacitors, including normal capacitors, normal capacitors attenuated by 20%, 40%, 60%, and 80%, and failed capacitors. The specifications of these six types of capacitors are shown in Table 1. Among them, capacitors of a normal capacitor state are normal capacitors of 45 \( \mu F \) capacitance and are able to run normally when delivered; capacitors of the attenuated capacitor state are normal capacitors attenuated by 20%, 40%, 60%, and 80%; and capacitors of the failed capacitor state are faulty, invalid, and disused capacitors due to expansion, burst, and casing puncture of 26 \( \mu F \) capacitance.

For the pre-treatment of capacitors, normal capacitors were attenuated by 20% and 40% by Shihlin Electric Machinery Co., Ltd. in its plant after the aging test, and capacitor banks abandoned after electrical accidents were used as failed capacitors (including capacitors of expansion, burst, and casing puncture). To analyse serious capacitor attenuation caused by long-term failure, capacitors were connected in series in the study to build the 60% and 80% attenuated capacitor models. Figure 3 shows independent capacitors in a normal state. Figure 4 presents the attenuation of normal capacitors for 20%, 40%, 60%, and 80%. The normal capacitor with an attenuation of 60% was connected to two 36 \( \mu F \) capacitors, while the normal capacitor with an attenuation of 80% was five 45 \( \mu F \) capacitors in series. Figure 5 illustrates the failed capacitors due to expansion, burst, and casing puncture.
TABLE 1  Power capacitor specifications

| Capacitor state | Capacitance | Phase   | Frequency | Rated voltage |
|-----------------|-------------|---------|-----------|--------------|
| Normal          | 45 µF       | Single-phase | 60 Hz   | 440 V        |
| 20% attenuation | 36 µF       | Single-phase | 60 Hz   | 440 V        |
| 40% attenuation | 27 µF       | Single-phase | 60 Hz   | 440 V        |
| 60% attenuation | 18 µF       | Single-phase | 60 Hz   | 440 V        |
| 80% attenuation | 9 µF        | Single-phase | 60 Hz   | 440 V        |
| Failure         | 26 pF       |          |           |              |

FIGURE 4  Attenuated capacitors

FIGURE 5  Failed capacitors

2.2  Self-made detection circuit design

In the actual measurement of the discharge signal of a power capacitor, the data volume is huge, as the extracted discharge signal has a long period and high frequency. In addition, the discharge voltage amplitude is small and there is too much electrical noise interference during the test [23], thus making it difficult to identify the discharge signal. Therefore, in order to effectively extract the high frequency signal from the discharge signal, the low frequency signal and noise was filtered out by using a high-pass filter [24]. The discharge voltage amplitude was amplified by a non-inverting amplifier so as to recognize the signal accurately. The physical circuit structure is shown in Figure 6.

3  THE PROPOSED METHODS

3.1  Empirical mode decomposition

This study used the Empirical Mode Decomposition (EMD) [25, 26] to transform the measured electrical signals. Different frequency components of the signals were effectively separated from the time curve in the form of Intrinsic Mode Functions (IMF), and the composition of the original signal in different frequency bands was drawn by the reconstruction. The important information implied in the original signal could be extracted in the signal decomposition process. First, all the extreme point values in \( x(t) \) are determined, wherein \( x(t) \) is the time sequence signal, and all the extreme points are combined by the curve to obtain the upper and lower envelopes of signal \( x(t) \), which are set as \( u_0(t) \) and \( v_0(t) \) respectively. The upper and lower envelope mean curve are expressed as Equation (1):

\[
m_0(t) = \frac{1}{2} [u_0(t) + v_0(t)]
\]
$m_0(t)$ is subtracted from $x(t)$ to obtain $b_1(t) = x(t) - m_0(t)$, and the function may or may not be an IMF component. In a general way, the function does not meet the requirements of the IMF: $x_1(t)$ can be replaced by $b_1(t)$, and $m_0(t)$ and $r_0(t)$ can be obtained and expressed as Equation (2):

$$
\begin{align*}
& m_1(t) = \frac{1}{2} [x_1(t) + v_1(t)] \\
& b_2(t) = b_1(t) - m_1(t) \\
& \vdots \\
& m_{k-1}(t) = \frac{1}{2} [u_{k-1}(t) + r_{k-1}(t)] \\
& b_k(t) = b_{k-1}(t) - m_{k-1}(t)
\end{align*}
$$

After the above decomposition process is performed multiple times and a certain standard is reached, $b_k(t)$ becomes the first IMF of the original signal, which is set as $y_1(t)$, and the rest of the signal is set as $r_1(t)$ and expressed as Equation (3):

$$
\begin{align*}
& y_1(t) = b_k(t) \\
& r_1(t) = x(t) - y_1(t)
\end{align*}
$$

where $y_1(t)$ is the first component derived from the original data, which means that it is the highest frequency component in the original signal $x(t)$, and $r_1(t)$ is the corresponding residual component. Next, the rest of $r_1(t)$ is used as a new original signal, and the calculation processes of Equations (2) and (3) are repeated. The second IMF $y_2(t)$ can be obtained, and this is repeated $n$ times until the remainder is a monotonic signal or has a value smaller than the given value. The decomposition is then completed, and the nth IMF $y_n(t)$ and residual component $r_n(t)$ are obtained and expressed as Equation (4):

$$
\begin{align*}
& r_1(t) - y_2(t) = r_2(t) \\
& \vdots \\
& r_{n-1}(t) - y_n(t) = r_n(t)
\end{align*}
$$

Therefore, the important information in the fault signal can be extracted by the repeated decomposition of the EMD, and the noise can be eliminated.

### 3.2 Chaos synchronisation detection

The chaos theory was proposed by the American meteorologist, Edward Norton Lorenz [27]. Chaos phenomena are characteristic of the nonlinear system theory. In the chaotic synchronisation signal system, the chaos system is divided into the Master System (MS) and the Slave System (SS). When the two systems receive different signals, the kinematic trajectory will have different dynamic errors, therefore the SS follows the MS, which is known as a chaotic synchronisation action [28].

The dynamic error of natural chase in the master and slave synchronisation systems is used for the captured capacitor discharge signal to extract the dynamic error between the two systems, resulting in different operating trajectories. The Lorenz chaos system used in this paper is divided into the master and slave chaotic systems, and are expressed as Equations (5) and (6):

$$
\begin{align*}
& L_{master} = \begin{cases}
\dot{x}_1 = \alpha(x_2 - x_1) \\
\dot{x}_2 = \beta x_1 - x_1 x_3 - x_2 \\
\dot{x}_3 = x_1 x_2 - \gamma x_3
% \end{cases} \\
& L_{slave} = \begin{cases}
\dot{y}_1 = \alpha(y_2 - y_1) \\
\dot{y}_2 = \beta y_1 - y_1 y_3 - y_2 \\
\dot{y}_3 = y_1 y_2 - \gamma y_3
% \end{cases}
\end{align*}
$$

Equation (6) is subtracted from Equation (5), and computation is performed to obtain the dynamic error equation of the Lorenz master and slave chaotic systems, which is expressed as Equation (7):

$$
\begin{align*}
& e_1 = \begin{bmatrix}
-\alpha & 0 & 0 \\
-\beta & -1 & 0 \\
0 & 0 & -\gamma
% \end{bmatrix}
\begin{bmatrix}
e_1 \\
e_2 \\
e_3
% \end{bmatrix}
+ \begin{bmatrix}
0 & \gamma y_3 - x_2 x_3 \\
\gamma x_3 + x_1 x_3 \\
\gamma y_2 - x_1 x_2
% \end{bmatrix}
\end{align*}
$$

where $x$ is set as MS and the initial value is set as 0; $y$ is set as SS, and its value is the capacitor discharge current value, $\alpha, \beta$, and $\gamma$ are the coefficients of the adjustment error, in which $\alpha = 10$, $\beta = 28$, and $\gamma = (-8/3)$; and the chaos error signals $e_1, e_2$, and $e_3$ of the Lorenz master and slave chaotic systems can be derived from this group of error coefficients.

### 3.3 Convolutional neural network

The Convolutional Neural Network (CNN) is an extensively-used supervised learning image classifier. It is defined as a part of deep learning network, and has a high accuracy for image classification [29]. Common pre-trained models include GoogLeNet [30], ResNet [31], AlexNet [32], and VGG [33]. The main architecture is comprised of a convolutional layer with an activation function, a pooling layer, and a fully-connected layer [34, 35], which this section discusses. The CNN architecture of this proposed study is shown in Figure 7. The image feature is extracted by using one input layer, two convolutional layers, and two pooling layers, and then the recognition of the power capacitor fault type is implemented via operations of the neural network composed of a flatten layer, hidden layer, and output layer in the fully-connected layer.

#### 3.3.1 Convolution layer

The convolutional layer extracts features in the network. The layer uses masks of different sizes for the convolution operation. Spatial filtering is used for image feature extraction or feature enhancement. This study uses a $3 \times 3$ mask (convolution kernel) for convolution operation and illustrates the example of
the convolution operation proposed in Figure 8. If the original image is a 5 × 5 image and a 3 × 3 mask, then the mask performs a convolution operation for the original image step by step until the original image is operated by the mask. The feature image can then be obtained at last.

The activation function is applied after the convolution operation for non-linear mapping of the output result of the convolutional layer before the next stage starts. Common activation functions include the Sigmoid and the ReLu series; however, the gradient loss of the Sigmoid series gets worse as the number of iterations increases. Thus, this study used ReLu as the non-linear function, which is expressed as Equation (8):

\[
f(x) = \begin{cases} 
0, & \text{if } x < 0 \\
 x, & \text{if } x \geq 0
\end{cases}
\]  

(8)

where \(x\) is the output of the previous neuron. If \(x < 0\), then the output of the non-linear function is 0; if \(x \geq 0\), then the input of the non-linear function is equal to the output.

### 3.3.2 Pooling layer

When the feature is obtained by the convolutional layer, the pooling layer is applied after feature extraction, in order to effectively reduce the feature size with minimum influence on the eigenvalue. It can reduce the computation complexity of the entire network. The pooling layer is divided into the max pooling layer and the average pooling layer. The max pooling computing mode uses a colour block as a unit to obtain the maximum value, so as to obtain the max pooling output. The average pooling is similar to max pooling, and a colour block from a previous image is used as a unit and averaged to obtain the average pooling output. This study uses the 2 × 2 max-pooling method for operations. According to the example of operations in Figure 9, if the feature image (6 × 6) is segmented by 2 × 2 blocks, then the maximum value of each colour block is taken, and the dimension reduction image (3 × 3) output is obtained at last.

### 3.3.3 Full-connected layer

The full-connected layer refers to the conventional neural network model, often to the end of convolutional neural network. The matrix of the image features extracted by the front-end convolutional layer and pooling layer is converted into a one-dimensional vector that is imported into the neural network. The neural network training is then performed by Backpropagation. Finally, the output layer generates the image classification result. Figure 10 presents the architecture of the full-connected layer proposed in this paper. If the flatten layer has \(iX\) neurons, the hidden layer has \(kH\) neurons, and the output layer has \(jY\) neurons, where \(W_{XH}\) is the weight of the relationship between the flatten layer and hidden layer, and \(W_{HY}\) is the weight of the
relationship between the hidden layer and output layer. Equation (9) expresses the relation of the flatten layer and hidden layer of the full-connected layer, and Equation (10) shows the relation of the hidden layer and output layer.

\[ H_k = \sum_{i=1}^{k} X_i \times WXH[i][k] \]  

(9)

\[ Y_j = \sum_{k=1}^{j} H_k \times WHY[k][j] \]  

(10)

4  | ACTUAL MEASUREMENT AND RESULT ANALYSIS

4.1  | Actual power capacitor measurement result

The discharge data of the power capacitors measured in this study were based on three cycles of the mains supply (110 V, 60 Hz). Five attenuated capacitor defect states and a normal capacitor state were planned for a total of six types. The extraction time for each type of discharge data was 50 ms, the sampling frequency was 20 MS/s, and the number of sampling points was 1,000,000. The current signal of the power capacitor was pre-processed by a high-pass filter circuit and a non-inverting amplifier circuit to obtain the discharge data, and then the waveform of the discharge data was decomposed by the empirical mode to obtain the IMF waveform. Figure 11 shows the original discharge waveform of the normal capacitor, the original discharge waveform of a normal capacitor with 20–80% attenuation, and the original discharge waveform of a failed capacitor. Figure 12 shows the IMF waveform of the normal capacitor, the IMF waveform of a normal capacitor with 20–80% attenuation, and the IMF waveform of a failed capacitor.

The six waveforms of the power capacitors obtained by EMD were processed by using the Lorenz chaos synchronisation detection method to obtain the chaos dynamic error scatter map. The high-frequency IMF waveforms, IMF1–IMF5, could be derived from the EMD of the measured discharge signal, and the 3D chaos dynamic error scatter map could be obtained after the Lorenz master slave chaos system operation. Following that, the total mean percentage error (as Equation (11)) was used to calculate the distances between the left and right chaotic eyes, with the maximum distance selected as the feature signal.

\[ D = \sum_{i=1}^{n} \sqrt{ (X_i^L - X_i^R)^2 + (Y_i^L - Y_i^R)^2 + (Z_i^L - Z_i^R)^2 } \]  

(11)

\[ D: \] Distance between the left and right chaotic eyes  
\[ i: \] Discharge signal sample of the \( i \)th capacitor  
\[ n: \] Total number of discharge signal samples of capacitors  
\[ X_i^L: \] \( X \)-coordinate value of the left chaotic eye of the \( i \)th capacitor  
\[ Y_i^L: \] \( Y \)-coordinate value of the left chaotic eye of the \( i \)th capacitor
Table 2 shows the total mean percentage error and recognition rate of IMF1–IMF5. Figure 13 presents the scatter map of the chaotic dynamic errors of IMF1, where the distance between the left and right chaotic eyes is 2.2433 (the longest). Figure 14 illustrates the scatter map of the chaotic dynamic errors of IMF5, where the minimum distance between the left and right chaotic eyes is 0.6812 (the shortest).

According to the actual measurement and calculation analysis results, the IMF1 signal could identify the defective state of the power capacitor most effectively. Thus, this study used EMD to calculate the IMF1 waveform and to display the fault detection feature image of the 3D chaotic scatter diagram of the power capacitor. According to measure analysis, the 3D chaotic scatter diagrams resulting from different attenuation degrees of power capacitor have distinctly different shapes and distribution densities. Based on the aforementioned chaotic scatter characteristics, this paper uses CNN fit for image recognition for training and classification. The chaotic scatter feature images of the power capacitor is shown in Figures 15–20.

### 4.2 CNN recognition result

This study made 240 partial discharge samples of capacitors, with 40 for each of the six types of capacitors. As analysed...
by EMD and chaotic synchronization detection method, 40 3D scatter maps of chaotic dynamic errors were drawn for each type of capacitor, from which 30 were randomly selected as the training samples, and the remaining ten were used as CNN recognition samples. As shown in Figure 7, the CNN architecture used in this study has two convolutional layers, two pooling layers and one fully-connected layer, a $3 \times 3$ mask (convolution kernel), a ReLu activation function, and a $2 \times 2$ max pooling that were used to identify the type of faults of capacitors. The test environment is MATLAB 2020a with Intel Core (TM) i7-9700 CPU@3.0 GHz processor, NVIDIA GeForce RTX 2080 SUPER graphics card, along with Windows professional 64-bit operating system.

This study used MATLAB to develop the proposed algorithm, implemented the power capacitor fault diagnosis identification system, and collected thirty 3D chaos eye scatter images of various power capacitor types, with different fault types as the training image data, which were imported into the CNN architecture for training and learning. The training results showed 100% accuracy after 123 iterations of learning and the error rate was 0%, which means that the CNN had completed the training and learning. The training process curve is shown in Figure 21.
In order to validate that the trained network could identify the six types of power capacitors, 60 new 3D chaotic scatter images of power capacitor fault types, which are different from the training data images, were collected as the test image data, and the faults in the new data images for testing were classified by using the trained network model. Table 3 shows the classification and recognizes the results of the power capacitors, where it is observed that the proposed network can correctly identify and classify the types of power capacitors. The recognition accuracy rate was the high at 97%.

4.3 Comparison analysis of the proposed method and other algorithms

This study used the composed Back-Propagation Network (BPN), Learning Vector Quantization Network (LVQ), Probabilistic Neural Network (PNN), Extension Neural Network (ENN) and Extension theory for fault classification according to the training sample signal and test sample signal of the same power capacitor type, which are compared with the proposed method, in order for the superiority of the proposed method to be proved. Table 4 shows the power capacitor recognition comparison analysis. It was observed that the proposed CNN has better recognition results than the other algorithms. Because the CNN has automatic image feature extraction, noise reduction, the edge feature is extracted as the basis of recognition, and the characteristics of the important information of an image are maintained, while the CNN is able to recognize the image details with the convolution layer and pooling layer. Therefore, it is better than conventional artificial neural network algorithm which simply extracts numerical data for training and recognition operations.

Finally, 60 power capacitor test signal samples were mixed with noise 5% and 10% by a random number, to simulate the noise interference in the measurement of the discharge data of power capacitor in the course of power capacitor fault diagnosis. The recognition results after the addition of noise are concluded in Table 5. As seen, the accuracy of the proposed method with noise is still higher than 90%, compared to the other algorithms. Therefore, the power capacitor fault diagnosis recognition system proposed in this paper has a high recognition accuracy rate, as well as better resistance to noise than the other algorithms.

5 CONCLUSION

This study examined normal capacitors and the fault detection of power capacitors with different attenuation degrees (20%, 40%, 60%, 80%, and failure). The faults were divided into six types. EMD and the chaos synchronisation detection method were used to establish the chaos dynamic error scatter map of the partial discharge signals for the power capacitors. The 3D scatter image was used as an important basis for the fault features. The advantages of this method are that mass data could be compressed effectively and that specific feature images could be extracted. Finally, fault type image learning and recognition were
performed directly by CNN. The experimental results showed that the accuracy of the proposed CNN method is as high as 97% and has the high efficiency of noise rejection ability, which proves that the proposed method is effective for power capacitor fault detection. In addition, the proposed method can be used in the future to detect faults in capacitors as well as in power-related equipment, such as transformers, electric motors, generators, etc.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the financial support of the Ministry of Science and Technology of Taiwan (R.O.C.) under grant numbers MOST 109-2221-E-167-009 and MOST 108-2221-E-167-018-MY2.

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How to cite this article: Lu S-D, Sian H-W, Wang M-H, Kuo C-C. Fault diagnosis of power capacitors using a convolutional neural network combined with the chaotic synchronisation method and the empirical mode decomposition method. IET Sci Meas Technol. IET Sci Meas Technol. 2021;1–11. https://doi.org/10.1049/smt2.12056.