

Partial Discharge Pattern Recognition of Current Transformers Using an ENN

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Abstract—This paper proposes an extension-neural-network (ENN)-based recognition method to identify the partial-discharge (PD) patterns of high-voltage current transformers (HVCTs). First, a commercial PD detector is used to measure the three-dimensional (3D) PD patterns of cast-resin HVCTs, then three data preprocessing schemes that extract relevant features from the raw 3-D PD patterns are presented for the proposed ENN-based classifier. The ENN proposed in the author's recent paper citation combines the extension theory with a neural-network architecture. It uses extension distance instead of using Euclidean distance (ED) to measure similarities between tested data and cluster centers; it can implement supervised learning and give shorter learning times and simpler structures than traditional neural networks. Moreover, the ENN has the advantages of high accuracy and noise tolerance, which are useful in recognizing the PD patterns of electrical apparatus. To demonstrate the effectiveness of the proposed method, comparative studies with a multilayer multi-layer perceptron (MLP) are conducted on 150 sets of field-test PD patterns of HVCTs with rather encouraging results.

Index Terms—Current transformers (CTs), extension neural network (ENN), partial discharge (PD).

I. INTRODUCTION

HIGH-VOLTAGE insulation in operating electrical apparatus gradually deteriorates due to thermal, mechanical, electrical, and environmental stresses [1]. The high-voltage current transformer (HVCT) is essential equipment for measuring current signals in power systems. Failure of an HVCT may cause the wrong current signals, and cause a series of mistakes in power-supply operation. Therefore, it is of great importance to detect incipient failures in HVCTs as early as possible, so that they can be switched safely and improve the reliability of the power systems. Partial discharges (PDs) are a symptom and a cause of high insulation deterioration; it is a sudden local displacement of electrons and ions in an insulator under the pressure of a strong electric field [2]–[4]. The quantities of PD can carry information about insulating system conditions to the outside world by electrical signals. PD testing is an important tool for the implementation of predictive or condition-based maintenance. Therefore, measuring and recognition techniques for PD patterns in electrical apparatus have attracted considerable attention from electrical manufacturers and power utilities [5]–[7].

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The main parameters of PD patterns are phase angle ϕ , discharge magnitude q , and frequency n [8], [9]. Recently, detailed and precise information about these quantities has become obtainable, and the three-dimensional (3-D) patterns have been shown by virtue of advanced measurement equipment with high-speed data processing. The shape of the PD pattern is characteristic for each type of defect. Therefore, an expert can use pattern recognition to identify the different defect types according to the 3-D pattern. The automated recognition of PD patterns has been widely studied recently. Various pattern recognition techniques have been proposed, including, expert systems [10], fuzzy clustering [11], and neural networks (NNs) [12]–[15]. The expert system and fuzzy approaches require human expertise, and have been successfully applied to this field. However, there are difficulties in acquiring knowledge and in maintaining the database. NNs can directly acquire experience from the training data, and overcome some of the shortcomings of the expert system. However, the training data must be sufficient and compatible to ensure proper training in traditional NN; its convergence of learning is influenced by the network topology and values of learning parameters. A further limitation of the traditional NN is the inability to produce linguistic output, because it is difficult to understand the content of network memory.

To improve the performances of traditional clustering technology, three preprocessing schemes that extract relevant features from the raw PD patterns with an extension-neural-network (ENN)-based clustering method are proposed for PD pattern recognition of HVCT in this article. The ENN has been proposed in the author's recent paper [16], [17]; it uses an extension distance instead of using Euclidean distance (ED) to measure the similarities between tested data and cluster domain. It can quickly and stably learn to categorize input patterns and permit adaptive processes to access significant new information. Moreover, the ENN has shorter learning times and a simpler structure than traditional NNs. To demonstrate the effectiveness of the proposed method, 150 sets of field-test PD patterns from 23-kV cast-resin type CTs were tested. Results of the studied cases show that the proposed method is suitable as a practical solution.

II. THEORY OF THE ENN

In this world, there are some clustering problems where features are defined as a range of values. For example, the safe operation voltages of a specified motor may be between 200 and 240 V. Younger can be defined as a cluster of people between the ages of 14 and 24. These problems are difficult to implement with appropriate clustering methods by current NNs.

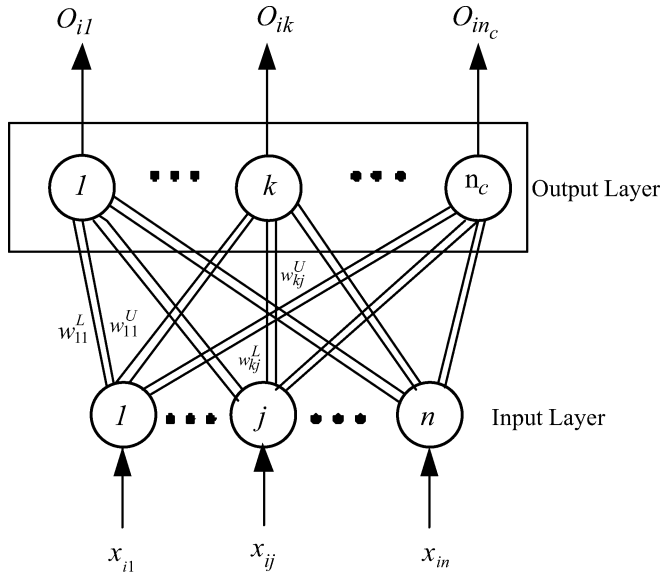


Fig. 1. Structure of extension neural network (ENN).

Therefore, a new topology of neural networks, called ENN that combines extension theory [18] with NNs, has been proposed to solve these problems [16], [17]. In other words, the ENN permits that clustering problems have a range of features, supervised learning, continuous input, and discrete output. This new NN is a first combination of extension set theory and NN. The extension theory provides a novel distance measurement for classification, and the NN can embed the salient features of parallel computation power and learning capability.

A. Structure of the ENN

In this clustering problem of PD recognition, PD features and associated defect types cover a range of values. Therefore, using the ENN is most appropriate for PD recognition of HVCTs. The schematic structure of the ENN is depicted in Fig. 1. It comprises the input layer and the output layer. The nodes in the input layer receive the input features and use a set of weighted parameters to generate an image of the input pattern. In this network, there are two connection values (weights) between input nodes and output nodes; one connection represents the lower bound, and the other connection represents the upper bound for this classical domain of the features. The connections between the j th input node and the k th output node are w_{kj}^L and w_{kj}^U . This image is further enhanced in the process characterized by the output layer. The output layer is a competitive layer. There is one node in the output layer for each prototype pattern, and only one output node with nonzero output to indicate the prototype pattern that is closest to the input vector. The operation mode of the proposed ENN can be separated into the learning phase and the operation phase. The learning algorithm of the ENN is discussed in the next section.

B. Learning Algorithm of the ENN

The learning of the ENN can be seen as supervised learning; the purpose of learning is to tune the weights of the ENN to achieve good clustering performance or to minimize the clustering error. Before the learning, several variables have to be de-

finied. Let the training set $\{X_1, T_1\}, \{X_2, T_2\}, \dots, \{X_Q, T_Q\}$, where Q is the total number of training patterns, X_i is an input vector to the NN and T_i is the corresponding target output. The i th input vector is $X_i \equiv \{x_{i1}, x_{i2}, \dots, x_{in}\}$, where n is the total number of the features. To evaluate the learning performance, the error function is defined as

$$E_t = \frac{1}{2} \sum_{i=1}^Q \sum_{j=1}^{n_c} (t_{ij} - o_{ij})^2 \tag{1}$$

where t_{ij} represents the desired j th output for the i th input pattern, O_{ij} represents the actual j th output for the i th input pattern. The detailed supervised learning algorithm can be described as follows:

- Step 1) Set the connection weights between input nodes and output nodes according to the range of classical domains. The range of classical domains can be directly obtained from previous experience, or determined from training data as follows:

$$\begin{aligned} w_{kj}^L &= \min_{T_i \in k} \{x_{ij}\} \\ w_{kj}^U &= \max_{T_i \in k} \{x_{ij}\} \\ &\text{for } i = 1, 2, \dots, Q; \quad j = 1, 2, \dots, n; \\ &\quad k = 1, 2, \dots, n_c. \end{aligned} \tag{2}$$

- Step 2) Read the i th training pattern and its cluster number p

$$X_i = \{x_{i1}, x_{i2}, \dots, x_{in}\}. \tag{4}$$

- Step 3) Use the extension distance to calculate the distance between the input pattern X_i and the k th cluster as follows:

$$ED_{ik} = \sum_{j=1}^n \left(\frac{\left| x_{ij} - \frac{(w_{kj}^U + w_{kj}^L)}{2} \right| - \frac{(w_{kj}^U - w_{kj}^L)}{2}}{\frac{(w_{kj}^U - w_{kj}^L)}{2}} + 1 \right), \tag{5}$$

for $k = 1, 2, \dots, n_c$.

The proposed extension distance is a new distance measurement; it can be graphically presented as in Fig. 2. The proposed ED can describe the distance between the x and a range $\langle w^L, w^U \rangle$, which is different from the traditional Euclidean distance. From Fig. 2, we can see that different ranges of classical domains can arrive at different distances due to different sensitivities. This is a significant advantage in classification applications. Usually, if the feature covers a large range, the data requirement is fuzzy or low in sensitivity to distance. On the other hand, if the feature covers a small range, the data precision requirement and sensitivity to distance are high.

- Step 4) Find the m , such that $ED_{im} = \min\{ED_{ik}\}$. If $m = p$, then go to Step 6; otherwise, go to Step 5.

- Step 5) Update the weights of the p th and the m th clusters as follows:

$$\begin{cases} w_{pj}^{L(\text{new})} = w_{pj}^{L(\text{old})} + \eta \left(x_{ij} - \frac{w_{pj}^{L(\text{old})} + w_{pj}^{U(\text{old})}}{2} \right) \\ w_{pj}^{U(\text{new})} = w_{pj}^{U(\text{old})} + \eta \left(x_{ij} - \frac{w_{pj}^{L(\text{old})} + w_{pj}^{U(\text{old})}}{2} \right) \end{cases} \tag{6}$$

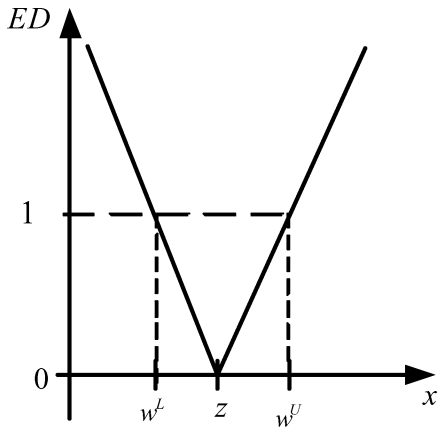


Fig. 2. Proposed extension distance (ED).

$$\begin{cases} w_{mj}^{L(new)} = w_{mj}^{L(old)} - \eta \left(x_{ij} - \frac{w_{mj}^{L(old)} + w_{mj}^{U(old)}}{2} \right) \\ w_{mj}^{U(new)} = w_{mj}^{U(old)} - \eta \left(x_{ij} - \frac{w_{mj}^{L(old)} + w_{mj}^{U(old)}}{2} \right) \end{cases},$$

for $j = 1, 2, \dots, n_c$ (7)

where η is a learning rate, set to 0.1 in this paper. From this step, we can clearly see that the learning process is only to adjust the weights of the p th and the m th clusters.

- Step 6) Repeat Steps 2–5, if all patterns have been classified; then a learning epoch is finished.
- Step 7) Stop, if the clustering process has converged, or the total error has arrived at a preset value; otherwise, return to Step 3.

It should be noted that the proposed ENN can take human expertise before the learning, and it can also produce meaningful output after the learning, because the classified boundaries of the features are clearly determined.

C. Operation Phase of the ENN

- Step 1) Read the weight matrix of the ENN.
- Step 2) Read a testing pattern

$$X_t = \{x_{t1}, x_{t2}, \dots, x_{tn}\}. \quad (8)$$

- Step 3) Use the proposed extension distance (ED) to calculate the distance between the tested pattern and every existing cluster by (5).
- Step 4) Find the m , such that $ED_{im} = \min\{ED_{ik}\}$, and set the $O_{im} = 1$ to indicate the cluster of the tested pattern.
- Step 5) Stop, if all of the tested patterns have been classified; otherwise, go to Step 2.

III. ENN-BASED PD PATTERN RECOGNITION SCHEMES

A. PD Measuring System

According to the IEC60270 standard [19], a partial-discharge measuring system for HVCTs has been set up in the Taiwan Electric Research and Testing Center (TERTC), an independent electrical testing institute in Taiwan. The structure of the PD measuring system is shown in Fig. 3. It includes a commercial

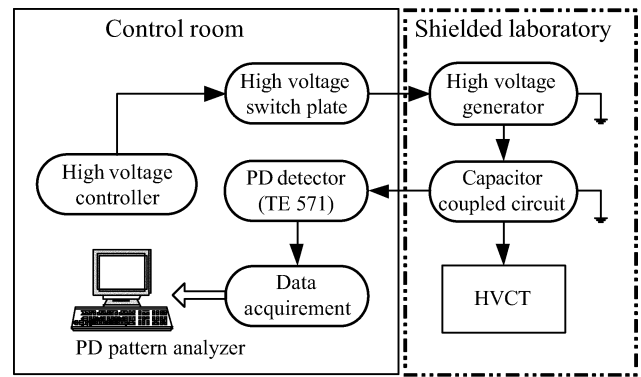


Fig. 3. PD measuring system diagram.

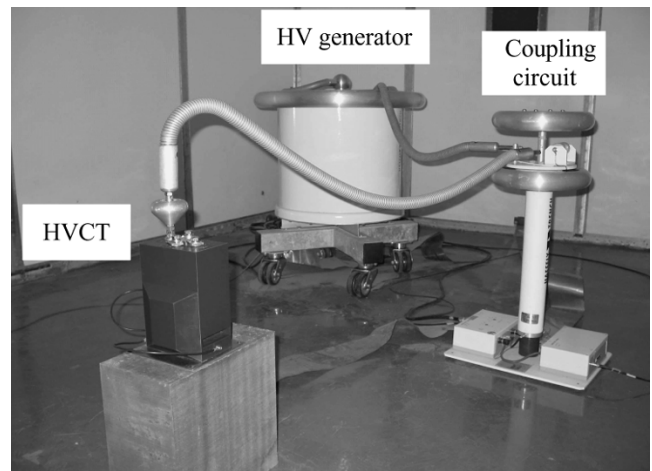


Fig. 4. Practical experimental circuits of HVCT PD test.

PD detector (TE 571), PD pattern analyzer' capacitor coupling circuit, a high-voltage control system, and the tested HVCT. The practical experimental circuit in the shielded laboratory is shown in Fig. 4. In this paper, the tested object is an EWF-20DB type of cast-resin HVCT that uses epoxy resin for HV insulation. The rated voltage and current of the tested HVCT are 23 kV and 60 A/5 A, respectively. For testing purposes, four experimental models of cast-resin HCVTs with artificial insulation defects were purposely manufactured by an electrical manufacturer. The four PD models include no defect, HV corona discharge, low-voltage (LV) coil PD, and high-voltage (HV) coil PD. Fig. 5 shows a typical PD waveform in the window of the PD detector, which is most useful for an experienced maintained engineer. In the testing process, all of the measuring data are digitally converted in order to store them in the computer memory. Then, the PD pattern analyzer can automatically recognize the different defect types of the testing objects according to the digital PD signal with the setup program.

B. PD Pattern Preprocessing

The basic parameters to characterize PD patterns are phase angle ϕ , discharge magnitude q , and frequency n . These quantities can be performed 3-D patterns by virtue of advanced programs, such as MATLAB. In previous studies, directly using the matrix's values of 3-D patterns with the ANN for PD recognition [14], the main drawbacks are that the structure of the ANN

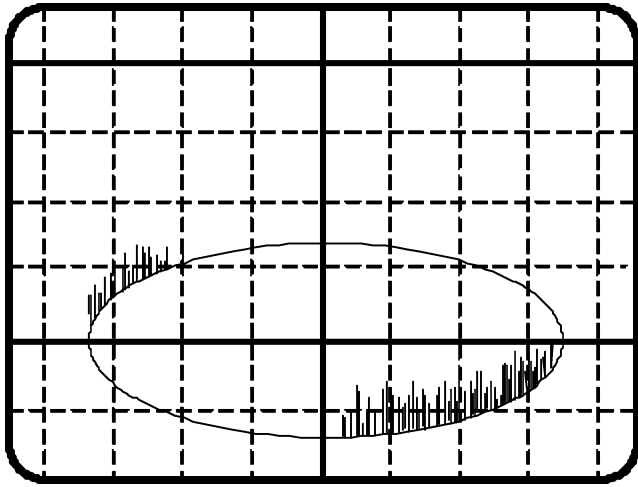


Fig. 5. Typical PD waveform.

has a great number of neurons with connections, and time-consuming in training. To improve the performance, three preprocessing schemes that extract relevant features from the raw PD patterns are presented for the proposed ENN-based classifier. The detailed data process is shown in Fig. 6; the output vector of the ENN-based classifier is the defect type of the PD pattern, and the input vector is the values of ten phase windows. The width of the phase window is set to 36°. The values of every phase window can be calculated as follows:

Scheme I) mean value of the total discharge magnitude

$$x = \frac{\sum_{j=1}^m \sum_{k=1}^n q_j n_{jk}}{\sum_{j=1}^m \sum_{k=1}^n n_{jk}} \quad (9)$$

Scheme II) mean value of the maximum discharge magnitude

$$x = \frac{\sum_{j=1}^m q_j n_{j \max}}{\sum_{j=1}^m n_{j \max}} \quad (10)$$

$$n_{j \max} = \max\{n_{jk}\}, \text{ for } k = 1, 2, \dots, n. \quad (11)$$

Scheme III) maximum discharge magnitude

$$x = q_{j^*} \times n_{j^* \max} \quad (12)$$

$$n_{j^* \max} = \max\{n_{jk}\}, \text{ for } j = 1, 2, \dots, m; \quad (13)$$

$$k = 1, 2, \dots, n.$$

When the preprocessing of the PD pattern has been completed, then the learning and identifying stages of the ENN can be started for PD recognition.

C. ENN-Based PD Recognized Method (EPDRM)

The proposed EPDRM has been successfully implemented using PC-based software for PD recognition for HVCTs. The overall operation flowchart is shown in Fig. 7. Using the proposed EPDRM can be simply described as follows.

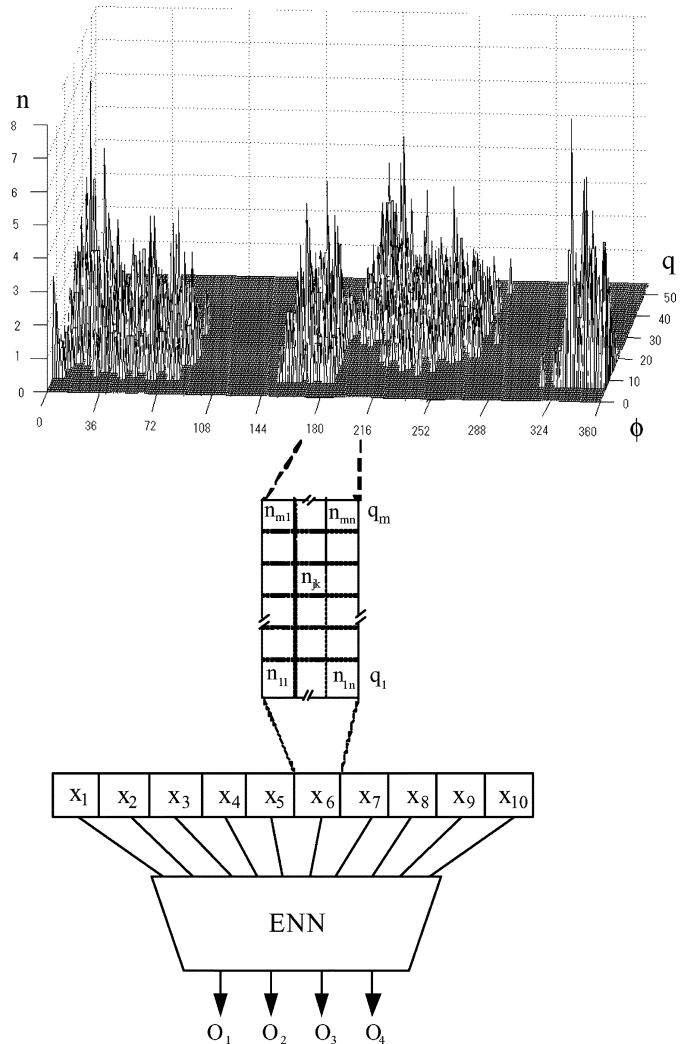


Fig. 6. PD pattern classification.

- Step 1) Set up the training pattern.
- Step 2) Set up the structure of the ENN that has ten input nodes and four output nodes in this paper.
- Step 3) Train the ENN using the proposed learning algorithm in Section II-B.
- Step 4) Go to Step 3, if the training process is not finished; otherwise, go to Step 5.
- Step 5) Save the weight vector of the trained ENN.
- Step 6) Use the trained ENN to identify the defect types of HVCTs.

Basically, the learning time of the EPDRM is shorter than the traditional neural-based methods due to the fact that initial weights of ENN can be directly determined from training data according to the upper bound and lower bound of input features of PD pattern.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

To demonstrate the proposed method, 150 sets of field test PD patterns were used to test the proposed EPDRM, the four defect models of 23-kV cast-resin HVCTs include the no-defect, HV

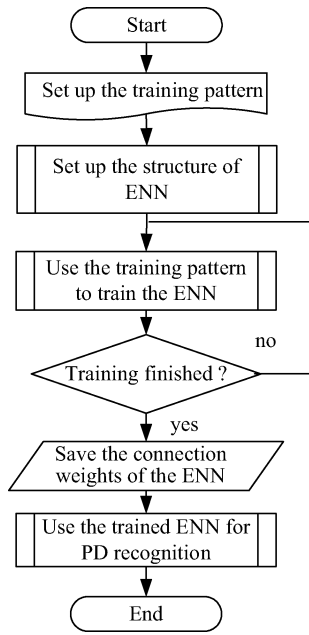


Fig. 7. Overall operation flowchart of the EPDRM.

corona discharge, LV coil PD, and HV coil PD. Some experimental results are shown as follows.

A. Results of the Data Preprocessing

As stated in Section III-B, Fig. 8 shows the typical input pattern of the four defect models, which have been processed by the three schemes. It should be noted that the input patterns of scheme I are similar to the input patterns of scheme II, and the four defect models have quite different patterns through data processing. Usually, the input patterns of no defect have the lower discharge magnitude than the other PD defects in all observed phase windows; the HV corona discharge has a higher discharge magnitude for the 7 and 8 windows. The LV coil PD has the higher discharge magnitude for the 1–3 and 5–8 windows. Conversely, the HV coil PD has the higher discharge magnitude for the 1–3, 5–8, and 10 windows. These features of input patterns will be most useful for PD recognition. To compare the three schemes, if the ENN-based PD recognition system randomly chooses 80 instances from the field-test data as the training data set, and the rest of the instances of the field-test data are the testing data set. Table I shows the recognized results of the proposed EPDRM with different input patterns. It is clear that the accuracy rates of the proposed EPDRM are quite high with about 100% and 97% for training and testing sets, respectively. It is obvious that the ENN has strong generalized capability. The recognized results of schemes I and II are almost of the same accuracy due to similar input patterns.

B. Performance Evaluation of the Proposed EPDRM

To evaluate the performance of the proposed EPDRM, Table II shows the comparison of the experimental results of the proposed method with the MLP-based method [14] that is directly using the matrix’s values of 3-D pattern for PD recognition. It should be noted that the structure of the proposed ENN is very simple, only 14 nodes and 80 connections are

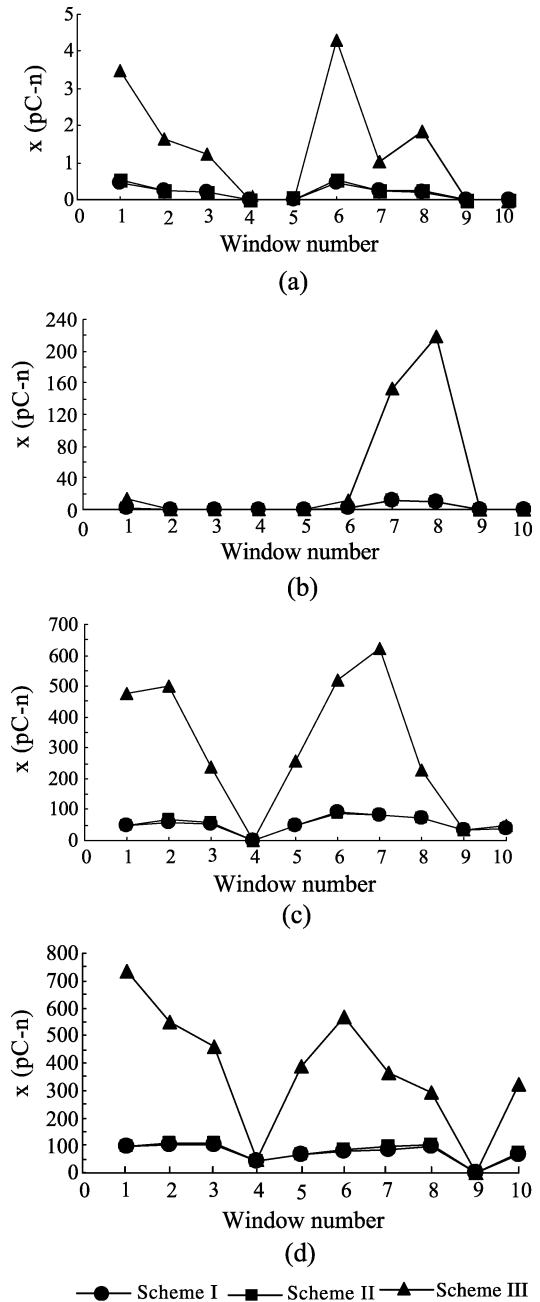


Fig. 8. Typical input patterns of four PD defects. (a) No defect. (b) HV corona discharge. (c) LV coil PD. (d) HV coil PD.

TABLE I
TRAINING RESULTS FOR THE ENN WITH DIFFERENT INPUT PATTERNS

Data set	Training set		Testing set	
	Classification	Accuracy	Classification	Accuracy
Scheme I	80/80	100%	70/70	100%
Scheme II	80/80	100%	70/70	100%
Scheme III	80/80	100%	68/70	97%

needed. Contrarily, the structure of the MLP-based method needs about 444 nodes and 16 160 connections. Moreover, the proposed ENN-based method also permits fast adaptive processing for a large amount of training data or new information, because the learning of the ENN is only to tune lower bounds

TABLE II
COMPARISON OF THE CLASSIFICATION PERFORMANCE OF VARIOUS METHODS

Compare item	Diagnosis methods	
	MLP [14]	ENN
Structure	400-40-4	10-4
No. of connections	16160.	80
Learning times (epochs)	3000.	1
CPU time (sec)	330	0.1
Learning Error E_t	4.6×10^{-7}	0.0

TABLE III
RECOGNIZED PERFORMANCES OF DIFFERENT METHODS
WITH DIFFERENT PERCENTAGES OF ERRORS ADDED

Error Percentage (%)	Accuracy of different recognized methods			
	MLP [14]	Proposed EPDRM		
		Scheme I	Scheme II	Scheme III
$\pm 0\%$	100%	100%	100%	100%
$\pm 5\%$	98%	100%	100%	98%
$\pm 10\%$	96%	100%	100%	98%
$\pm 15\%$	93%	99%	100%	95%
$\pm 20\%$	88%	96%	100%	93%
$\pm 25\%$	85%	92%	97%	92%
$\pm 30\%$	80%	89%	92%	89%

and upper bounds of the excited connections. On the other hand, the ENN is not only taking expert experience before learning, but can also produce meaningful output after learning, because the optimal classified boundaries of the features are clearly determined. It can be seen from Table II that the proposed ENN has a shorter learning time than the multilayer perceptron (MLP), the ENN only spends 1-epoch or 0.1 s of CPU time. Although the PD recognition system is trained offline, the training time is not a critical point to be evaluated. It is an index, however, implying in some degree the efficiency of the algorithm developed, which is rather beneficial when implementing the PD recognition methods in a microcomputer for a real-time PD detecting device or portable instrument.

C. Tests of Error-Containing Data

In this experiment, if the training data set contains 150 training instances (i.e., the full field-test data) and the testing data set is equal to the training data set, containing 150 training instances. The input data of a PD recognition system would unavoidably contain some noise and uncertainties. The sources of error include environmental noise, transducers, human mistakes, etc., which could lead to data uncertainties. To take into account the noise and uncertainties, 150 sets of testing data were created by adding $\pm 5\%$ to $\pm 30\%$ of random, uniformly distributed, error to the training data to appraise the fault-tolerant abilities of the proposed EPDRM. The test results using different amounts of errors added are given in Table III for the different recognition methods. Usually, the error containing data indeed degrades the recognition capabilities in proportion to the amounts of error added. This table shows that these methods all bear remarkable tolerance to the errors contained in the data. The proposed method with scheme II has a significantly higher recognition accuracy of 100% with $\pm 20\%$ errors added, but the accuracy of scheme III is lower than the

other schemes. However, the proposed methods show good tolerance to added errors, and have high accuracy rates of 89% and 92% in extreme error of $\pm 30\%$. Contrarily, the accuracy of the MLP-based method is only 80% under the same conditions.

V. CONCLUSION

This paper presents a novel PD recognition method based on the ENN for PD recognition of cast-resin HVCTs and three data preprocessed schemes for PD patterns. According to the experimental results, scheme II of data preprocessing is suggested for PD recognition due to the higher accuracy and error tolerances. Compared with the MLP-based recognition method, the structure of the ENN is simpler, and the learning time is faster than MLP-based method. Moreover, the proposed ENN-based recognition method also permits fast adaptive processing for a new PD defect, because it only tunes the boundaries of classified features or adds a new neural node. It is feasible to implement the proposed method on a microcomputer for a portable PD detecting device; it can be also used in the HV transformers and HVPT PD recognition if we can provide the sufficient training patterns. From the tested examples, the proposed method has a significantly high degree of recognition accuracy and shows good tolerance to errors added. This new approach merits more attention, because ENN deserves serious consideration as a tool in PD recognition problems. We hope this paper will lead to a further investigation for industrial applications.

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