A Top-down Approach to Partial Discharge Recognition of Current Transformers

Ying-Piao Kuo, Chun-Yao Lee, Jin-Wei Shiu, Hong-Chan Chang Department of Electrical Engineering National Taiwan University of Science and Technology 43, Sec. 4, Keelung Rd., Taipei, Taiwan, R.O.C.

Abstract: - This paper presents a partial discharge (PD) recognition procedure. The top-down approach discussed first how to make the tailor-made current transformer (CT) models, how to obtain the 3D patterns from the CT models in a magnetically shielded room, and finally how to apply of an artificial neural network (BPN) in recognition. Firstly, tailor-made cast-resin current transformers with insulating defects were made for testing. The testing used magnetically shielded room and a commercial PD detector system to obtain 3D patterns of four experimental models for recognition niche. Secondly, through preprocessed data originating from the detecting system, training data sets for a back-propagation artificial neural network are used to be PD recognition patterns in three kinds of defects of current transformers and in a perfect one. Finally, with a view to exploring applicability in the field, this research randomly selects different levels of noise to distort the original training and testing set. These distorted data sets are entered for testing. Research results show that, with 20% noise per discharge count, an 80% successful recognition rate is achieved.

Key-Words: Partial Discharge, Pattern Recognition, Back-propagation, Artificial Neural Network

1 Introduction

Technology advances keep boosting sophistication levels of electric power facilities. Maintenance requirement demands are rigorous. With power demand rising year by year, electrical stresses on insulating materials of facilities also rise. Frequent overloads shorten life spans of power facilities, as seen in the speeded-up aging of insulating materials and the increasing occurrences of unanticipated power failures. The semiconductor industry is booming and relies on a stable power supply to avoid possible tremendous losses from unexpected power cutoffs. Although maintenance routines for power supply facilities are regularly executed, a blind spot still exists therein; that is that regular routines fail to gauge the real levels of defects in insulating materials. Maintenance on a regular facility-power-off basis inevitably affects factory operations. Suppose an examination of insulating materials for defect levels on a facility-power-on basis became feasible. Hazards of unexpected power failures induced by facility disorders could then be immensely reduced. Since PD itself can reveal defect levels, we present a discussion of PD detecting and pattern recognition.

PD detecting has drawn attention and a great pool of research throughout the world in recent years and seen some accomplishments and breakthroughs. In 1993, H. Borsi discovered a temperature rise would bring down the inception voltage of coil partial discharge, and over heating would threaten the life spans of dry transformers [1]. In 1995, V. K. Agarwal, among others, found factors that cause power facility aging: electrical stress, thermal stress, mechanical stress, radiation and so forth. They argued that PD detecting in insulating agents boasts supreme sensitivity and remarkable accuracy [2]. PD detecting, hence, acts as the key indicator of power facility breakdowns. Pattern recognition in the past depended on expert judgments for classification and defect level determination. Such a process is unscientific and needs professional experience from years' practice. As a more scientific approach, to bypass human errors, this paper introduces and elaborates on how to collect experimental data and how to use BPN for pattern recognition [3].

2 **Problem Formulation**

PD data, if obtained from simulation testing, may differ from those derived from empirical research. This study uses empirical experimentation, and employs tailor-made cast-resin current transformers with designated defects. Four types of defects designed which include Model A: perfect product, Model B: high voltage corona discharge, Model C: low voltage coil partial discharge and Model D: high voltage coil partial discharge. To reduce interference from noise and to make a very high level of dependability, the experiment is conducted mainly in a control room and a magnetically shielded room.



Fig. 1. Basic diagram of the PD measuring system

2.1 Procedure of Testing

Fig.1 depicts the basic diagram of the PD measuring system. Its control room facilities are composed of a high voltage controller, PD detector, and a switch control panel. And its magnetically shielded room facilities are a high voltage generator, a capacitive voltage divider and a coupling device. For the first step of the whole PD detecting cycle, a specified high voltage is generated by the high voltage generator in the magnetically shielded room via the switch control panel in the control room. This high voltage is then applied to the subject, the current transformers. PD signals are retrieved from the capacitive voltage divider and the coupling device and sent back to the PD detector in the control room for recording [4].

Fig.2 is the equipment connection of High-voltage generator, of partial discharge, and of tailor-made current transformer in shielded room with low noise environment. Aiming the testing object, the testing specification is cast-resin current transformers EWF-20DB and Epoxy resin is the main material. The Rated maximum voltage is 23kV, the impulse voltage is 125kV, the primary current value is 60/30A, and secondary current value is 5A. Fig.3 illustrates the commonly detecting circuit with RLC impedance and charging capacity which characteristic is with low impedance as charging and with narrow bandwidth as detecting and thereby it is with high sensitivity [5]. Fig.4 illustrates the experiment procedure. High voltage controller, via switch control panel, orders high voltage generator to generate a high voltage, which delivers 34.5kV, 1.5 times as high as the maximum voltage of the current transformer, within 50 seconds, and holds for 1 minute and subsequently drops to 23kV in 20 seconds [5-7]. At the point, the detector starts to gauge PD for a session of 2 minutes. 20 minutes after the detecting finishes, the current transformers recuperate and the next stage of the experiment unfolds. It is for the purpose of exciting PD that 34.5kV is held for one minute. Voltage drops to 23kV in order for PD to continue and for the PD detector to



Fig. 2. The measurement equipment and placed in the shielded room measurement. Impedance



gauge and record. Each experiment renders a set of data. There are four kinds of discharge models; each model is experimented on 30 times. This experiment produces 120 sets of data, 80 and 40 of which is for training and for testing.

2.2 Tailor-made Models

As mentioned, this testing involved four tailor-made current transformer models which is model A:perfect product, model B:- high voltage corona discharge, model C:- low voltage coil partial discharge and model D:- high voltage coil partial discharge. Fig. 5 depicts the inner defect of model C and model D within 1.25mm wire of primary side and of secondary side respectively.

Therefore the particular defect must be made before case resining in manufacture procedure. To observe the characteristic patterns of four models, the converted 3D pattern for the Model A, the perfect product, as in Fig. 6, the PD under 1 pC scattered around from 0~360°. In Fig. 7, the 3D pattern for Model B- high voltage corona discharge, discharges of similar amounts of more than 10 pC cluster at 270°. It shares identical patterns with those corona discharge patterns found in most references. Fig. 8 shows the 3D pattern for Model C- low voltage coil partial discharge, where most PD is lower than 100 pC and largely in quadrants I and III. Fig. 9 shows the 3D pattern for Model D- high voltage coil partial discharge. The PD amounts are distributed broadly in the largest phase angle-most under 300 pC and in quadrants I and III. In the aforementioned 3D pattern, φ axis stands for the phase angle at PD onset, q axis PD amount, and *n* the discharge count against φ and q. Original 3D pattern data is retrieved from the PD detector and takes the form of a matrix. The row corresponds with phase angle φ and the column with discharge amount q. The matrix element comes up as discharge count n. The 120 sets of data vary in configuration, in the range 288x (29~57), and have to be processed before becoming input to BPN.



Fig. 5. Inner structure of tailor-made CT.(a) Secondary coil with 1.25mm wire (b) Primary coil with 1.25 mm wire



Fig. 6. Model A: Perfect pattern.



Fig. 7. Model B:- high voltage corona discharge pattern.



Fig. 8. Model C:- low voltage coil PD pattern.



Fig. 9. Model D - high voltage coil PD pattern.

3 Application of BPN to PD Pattern Recognition

3.1 Preprocessing Procedure for Training

To meet the needs of BPN input layers and to optimize the efficiency of BPN training, input data handling plays a vital role [8, 9]. In this study, the retrieved 3D pattern data went through 3-step processing before being used as BPN input layer data. This preprocessing is explained steps as follows:

Step 1: PD Data Acquisition

From the 3D patterns experiment, we collected raw data matrices and further defined the range and designation of each notation accordingly. The collected 120 sets of data matrices vary in configuration, in the range of $288 \times (29 \times 57)$. φ axis is the discharge phase angle 0° ~ 360° uniformly divided

into 288 units, each 1.25° . q axis is discharge amount from 0 pC to 392 pC sliced into 29~57 divisions, each of which equals the maximum discharge amount (q_{max}) divided by 29~57. n axis is the discharge count, also the matrix element value, 0~22.

Step 2 : Feature Extraction

We build an $M \times N$ matrix, where φ axis 0°~360° with each division 360°/M; q axis 0 pC~400 pC with each division 400/N. The original matrix is then compared with this new matrix. If the range of each division from the original matrix fits into that of the new matrix, the original element value can be entered into the new matrix. Further, this value is compared with the one previously filled in. The larger stays but the smaller is deleted. This is for simplifying the original matrix and filtering out low per-discharge-count noise.

Step 3 : Data Scaling

We scale the discharge count, n, of the new matrix to make new matrix elements valued between 0.1 and 0.9 so that BPN will tend to converge. Finally, we manage to align the new matrix elements in order from i=1, j=1 to i=M, i=N. They become tabulated data for the BPN.

3.2 PD Pattern Recognition Using BPN

The artificial neural network structure adopted by this paper is a three-layer feed-forward back propagation network (BPN), and applying Matlab 6.5 BPN toolbox to archive this recognition. The selection of suitable neuron numbers for the input layer and the hidden layer can be obtained from the following tests:

3.2.1 The investigation on the hidden layer's neuron number

In general, there are no standard methods for determining the hidden layer's neuron number, the number choosing for which can only be determined through experiments according to various problems [10]. This paper used 'point by point' method to describe the curve of MSE and training time and to observe which section is the advantage to be the hidden layer's neural network. When selecting 20 for M and N within the input layer, that means the input-layer neuron number is fixed at 400; if four is selected for the neuron number within the output layer, which stands for four kinds of PD models. For each training instance, this study requires the training to stop once the number of learning epochs reaches 3000. The relationship between mean square error and number of neurons in the hidden layer and the required training time for the entire artificial neural

network when the hidden layer's neuron number, H, is set at 10, 20, 30, 40, 50, 60 and 80 respectively. Fig. 10(a) shows the relationship between mean square error and number of neurons in the hidden layer and the required training time during network training with various hidden neuron numbers, H, within the hidden layer. From Fig. 10(a), we can see that if the neuron number in hidden layer is set at from 30 to 50, the mean square error in entire network will be smaller and the time used will be rather short. When 30 and 40 are selected for M and N, respectively, within the input layer, namely when the input-layer neuron number is fixed at 1200, selecting number 'four' for the neuron number within the output layer will represent four kinds of PD models. The relationship between mean square error and number of neurons in the hidden layer and the required training time for the entire artificial neural network when the neuron number, H, in hidden layer is set at 10, 30, 50, 70, 90 and 110 respectively is next investigated. Fig. 10(b) indicates the relationship between mean square error and number of neurons in the hidden layer and the required training time during the entire network training caused by the various neuron numbers, H, within the hidden layer. Hence, if the neuron number in hidden layer is set between 50 and 70, the entire network's mean square error is smaller and the training time is shorter.





Fig. 11. The mean square error after network training (a).base on φ axis division number M .(b). base on q axis division number N .

3.2.2 The investigation on the input layer's neuron number

Using Matlab 6.5 toolbox, BPN, the input-layer neuron number in this study is mainly controlled by $M \times N$, where M is the division number of the discharge angle φ axis, and N the division number of the discharge amount q axis. The relationship between mean square error and number of neurons in the hidden layer and the required training time for the entire artificial neural network when the neuron numbers, learning epochs and the network parameters in hidden layer and the output layer are fixed is then investigated. When 40 is selected for the neuron number within the hidden layer, number 'four', for the neuron number in the output layer, 3000 for learning epochs, The relationship between mean square error and number of neurons in the hidden layer and the required training time for the entire artificial neural network with M set at 10, 20, 30, 45 and 95 is then investigated. Fig. 11(a) shows the mean square error and the required time for the training process, corresponding to various division numbers M. From Fig. 11(a), it is seen that when the division number M of the input layer φ axis is set between 20 and 30, the entire network's mean square error will be very small and the time used for training will be rather short too. We then investigate with the identical method the relationship between mean square error and number of neurons in the hidden layer and the required training time for the entire artificial neural network when the N within the input layer is set at 10, 20, 40, 50 and 100 respectively.

Fig. 11(b) indicates the mean square error and the time required for the training process corresponding to various division numbers, N. Hence, if the input layer's N is set between 20 and 40, the entire network's mean square error will be rather small and the training time will be rather short too.

From the above experiments, it is seen that when the input-layer neuron number is set at 400 and 1200 respectively, the neuron number, H, in hidden layer may be selected in the range of 30 to 50 and 50 to 70 respectively, which will result in a tiny mean square error discrepancy and a rather short required training time for the entire artificial neural network. When the neuron number, H, hidden layer is set at 40, the input-layer neuron number $M \times N$ can be selected in a range of $M = 20 \sim 30$ and $N = 20 \sim 40$, which will have an excellent effect on the entire artificial neural network training and the required time will be extremely short. However, the input-layer neuron number probably depends on each case.

4 Results & Discussion

• Noise-free recognition results & discussion

120 sets of data obtained in a shielded room without noise distortion undergo BPN recognition, 80 of which are for training purposes, 40 for testing. Results show BPN recognizes four types of PD 100% correctly, namely (1,0,0,0), (0,1,0,0), (0,0,1,0) and (0,0,0,1). Distinct features make these four types of patterns an easy task, and guarantee a 100% recognition rate. The results provide the dependability of standard defect model using tailor-made current transformer instead of traditional assumption.

• Noise-corrupted recognition results & discussion

20 sets of data are randomly combined for testing from PD models A, B, C and D, including those used in training and those did not. They are distorted by 100 sets of random noise matrices. With noise per discharge count at 10%, 20%, 30% and 40% respectively, these 20 sets of data undergo BPN pattern recognition. Results are displayed and explained in Table 1, including comparison for noise distortion on pattern recognition. In each PD model, there are four outcomes specifically for noise at 10%, 20%, 30% and 40%. Fig. 12 illustrates in detail how noise distorts the PD models. The recognition rate per model deteriorates with random noise. In particular, the high voltage corona discharge model, named model B suffers the most and model D "High voltage coil PD" the least. From Fig. 12, we can see the effect of noise at 10%, 20%, 30% and 40%. With noise within 10%, the recognition rates hover over 90%; with noise within 20%, the recognition rates stay above 80%. With noise higher than 20%, the recognition rates for model A and model B worsen notably. It is the small PD distribution coverage of model A "Perfect product" and model B "High voltage corona discharge" that makes both susceptible to the effects of noise. Even worse, since most noise per discharge count lies beyond the scope of the noise-free 3D pattern, noise is sometimes in a position to easily alter the pattern and make recognition difficult. However, in some cases noise-present and noise-free patterns are hardly different, with noise overlapped and with part of the original pattern, the recognition rates are hence not subject to deterioration, "High voltage coil PD". The broad coverage of its pattern can guard against noise corruption.



Table 1 The recognition result under noise.



Fig. 12. Diagram of recognition rate

From this test of paper, it is noticed that when the artificial neural network recognition under no noise interference conditions in a lab is applied, the recognition rate is good. After adding random noises, the recognition result is greatly affected. As shown in Fig. 12, Model A and Model B are greatly influenced by noises respectively; if the noise exceeds 20%, the recognition rate of Model A and Model B will apparently deteriorate. If this method is to be applied to field measurement, further investigation in the noise filtering technique, which is vital, will be needed. From the recognition results, it is observed that noise influence is a key factor in field measurement.

5 Conclusion

The empirical experiment based on tailor-made cast-resin current transformers distinguishes itself from a simulation in its practicality. The process and experience of the experiment contribute considerably to practical PD detecting. Data is obtained through the procedures stipulated by R.O.C. national standard CNS11437 and IEC60044-1. To set reference values, all data collection follows one single route. Study of BPN application to PD pattern recognition from current transformers proves itself valid. In a magnetically shielded room, noise-free recognition rate is 100%. Noise per discharge count at 20%

lowers the recognition rate to 80%. We thus learn the relation between recognition rate and the degree of effects from noise. Noise may interfere with or overlap the PD pattern, and likewise influence the recognition rate. The research results are of importance for reference in field detecting. Nonetheless, there is a way to work before this method can be considered field practical. Our to-do list states that more data need to be collected from defective patterns and more appropriate filter techniques are adopted, in sound consideration of application context. Only by going through the list can we be assured of reliable recognition.

From the tailor-made models and shield room experiment, it is therefore an accurate practice to design the detecting system with a very high level of dependability, thereby choosing optimal recognition algorithm through the niche of built standard patterns will be cleared in future study.

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