DEVELOPMENT OF ON-LINE PD DIAGNOSTIC ALGORITHM FOR SINGLE-PHASE GIS AND THREE-PHASE GIS

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Abstract: The objective of this study is the development of on-line partial discharge diagnostic algorithm for single-phase and three-phase gas insulated switchgears. For this aim, partial discharge data, which have been reported to be the most vital defects in gas insulated switchgear under service, and noise data were acquired. Preprocessing was carried out to eliminate background noise from raw data using the histogram noise cutting method. The phase-independent partial discharge characteristics were extracted and partial discharge patterns were classified by the diagnostic algorithm based on the self-developed genetic algorithm-neural network program. The final decision was conducted to determine the ultimate diagnostic result. The result of this study was applied to on-site 170kV three-phase gas insulated switchgear in which partial discharge had occurred. The diagnosis result coincided exactly with the partial discharge source. It can be shown that the newly developed algorithm is proven to be appropriate for partial discharge diagnosis without any phase information and is also applicable to single-phase and three-phase gas insulated switchgears.

1 INTRODUCTION

Recently, the application of on-line preventive diagnostic systems for gas insulated switchgear (GIS) has been increased to maintain reliable electric power system under service. There are many studies for condition and monitoring techniques such as partial discharge (PD) analysis, lightning arrester leakage current detection, SF_6 gas pressure measurement, circuit breaker contact-point abrasion rate, location of insulation defects, etc. Among these techniques, this study describes the PD pattern recognition.

Artificial intelligence methods or theories including fuzzy logic, chaos theory, wavelet, fractal, and neural network have been applied for PD pattern recognition. When applying those artificial intelligence methods, one of the most important things is how to determine key features.

In general, the PD features for single-phase GIS have been extracted from phase characteristics of PD signals after synchronizing the phase with the applied voltage. However, a three-phase in one enclosure type GIS (three-phase GIS) is difficult to synchronize the phase with voltage related to PD occurrence. Thus, phase-independent algorithm is required to diagnose single-phase GIS and three-phase GIS.

2 PD PATTERN IDENTIFICATION PROCEDURE

A general GIS PD pattern identification procedure is shown in “Figure 1” [1]. It consists of five stages: PD data acquisition stage to procure PD signals and store it, preprocessing stage to remove background noise from raw data, feature extraction stage to extract phase-independent PD characteristics, diagnosis stage to classify PD patterns using the developed diagnostic algorithm based on the PD pattern database, and final decision stage to determine the ultimate diagnosis result.

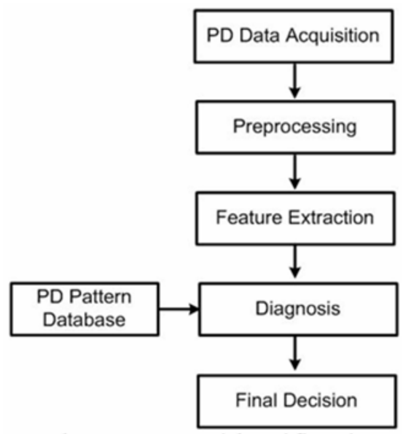

Figure 1: General PD pattern identification procedure

2.1 PD data acquisition

A real-scaled 70kV GIS, as shown in “Figure 2”, consists of high voltage bushing, two spacers and observation chamber where artificial defects were introduced for PD data acquisition. In order to detect PD, two methods were applied. One is by the UHF coupler mounted on the hatch plate of the observation chamber. HAFLEY TE571 according to IEC 60270 is another choice including relevant signal analysis. PD signals were transmitted to the analogue-digital conversion unit through a coaxial cable. And then the signals were transferred to the personal computer for data storage through LAN port.

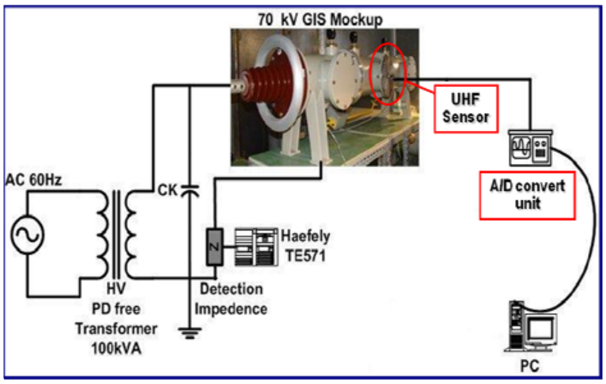

Figure 2: Block diagram of experimental setup

"Figure 3" shows the examples obtained by PD data acquisition test. Those are floating electrode, corona, free moving particle, and void in a spacer respectively.

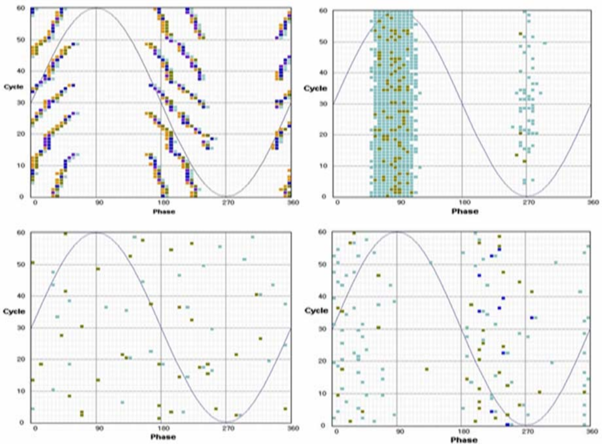

Figure 3: Examples of PD (top left: floating electrode, top right: corona, bottom left: free moving particle, bottom right: void in a spacer)

2.2 Preprocessing

Most of PD data include background noise which has lower magnitude than PD signals but cover almost all range of PD data. Thus, preprocessing stage is essential to reliable diagnosis.

PD data was transformed into ordinary histogram to analyze the frequency of PD data. Background noise level from histogram of PD data was computed by use of the preset frequency (Method 1) or the inflection point (Method 2). "Figure 5" shows the flowchart of preprocessing algorithm [2].

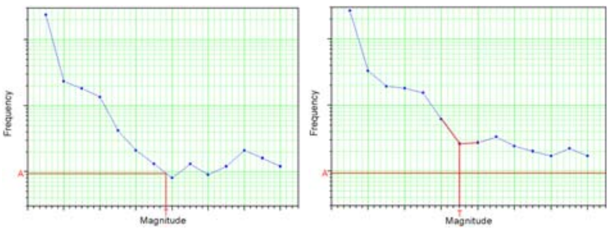

Figure 4: Calculation of background noise level (left: Method 1, right: Method 2)

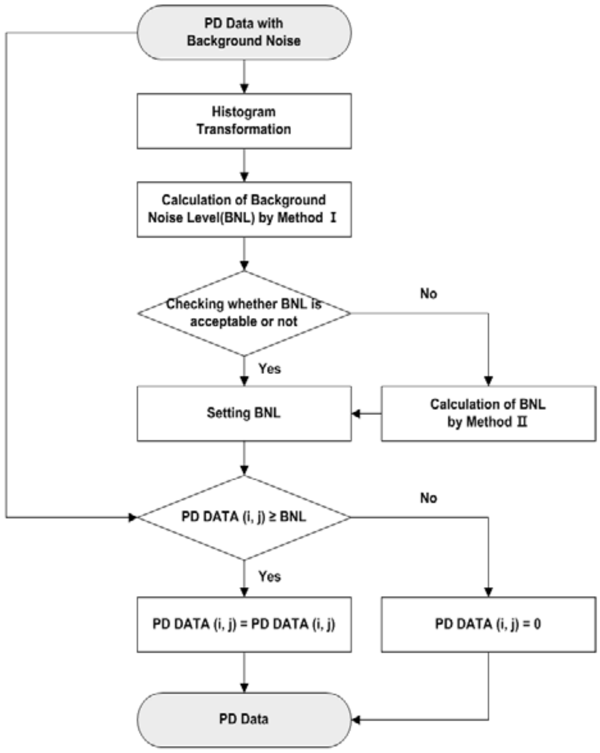

Figure 5: Flowchart of preprocessing algorithm

2.3 Feature extraction

Feature extraction stage is one of the most important parts of pattern recognition because it can directly influence a diagnosis result.

PD magnitude data $\mathrm{M_M}$ has $\mathrm{M}\times\mathrm{N}$ matrix where N covers the phase range and M covers the cycle range of PD data. In addition to the PD magnitude matrix, another PD matrix named PD occurrence matrix $\mathrm{M_O}$ was formulated by modifying the PD magnitude matrix. The PD occurrence matrix is necessary to compensate for the absence of phase characteristics of PD magnitude matrix and to diversify PD features.

The process of phase-independent feature extraction from PD matrix $\mathrm{M_M}$ and $\mathrm{M_O}$ is as follows:

① Construction of $1\times n$ row vector $\mathrm{rv_{M_j}}$, $\mathrm{rv_{O_j}}$ by summing each row from $\mathrm{M_M}$ and $\mathrm{M_O}$

$$\mathrm{rv_{M_j}}=\sum_{i=1}^{m}\mathrm{M_{M_{ij}}} \quad \text{for } j=1,\, 2,\, 3,\, \cdots,\, n$$

$$\overrightarrow{\mathrm{rv_M}}=[\mathrm{rv_{M_1}}\ \ \mathrm{rv_{M_2}}\ \ \mathrm{rv_{M_3}}\ \cdots\ \mathrm{rv_{M_n}}]$$

$$\mathrm{rv_{O_j}}=\sum_{i=1}^{m}\mathrm{M_{O_{ij}}} \quad \text{for } j=1,\, 2,\, 3,\, \cdots,\, n$$

$$\overrightarrow{\mathrm{rv_O}}=[\mathrm{rv_{O_1}}\ \ \mathrm{rv_{O_2}}\ \ \mathrm{rv_{O_3}}\ \cdots\ \mathrm{rv_{O_n}}]$$

② Construction of $m\times1$ column vector rv_{M_i}, rv_{O_i} by summing each column from M_M and M_O

$$cv_{M_i}=\sum_{j=1}^{n} M_{M_{ij}} \quad \text{for i=1, 2, 3, } \cdots \text{, m}$$
$$\overrightarrow{cv_M}=[cv_{M_1}\ cv_{M_2}\ cv_{M_3}\ \cdots\ cv_{M_m}]'$$

$$cv_{O_i}=\sum_{j=1}^{n} M_{O_{ij}} \quad \text{for i=1, 2, 3, } \cdots \text{, m}$$
$$\overrightarrow{cv_O}=[cv_{O_1}\ cv_{O_2}\ cv_{O_3}\ \cdots\ cv_{O_m}]'$$

Based on the row and column vector calculated from two PD matrices, the three kinds of phase-independent features were extracted as shown in table 1 below.

Table 1: Phase-independent PD features

PD matrix	Vector formulation	Extracted features		
		Statistical features	Texture features	Other features
PD magnitude matrix	Row vector	Average; Covariance; Skewness; Kurtosis; etc	Entropy; etc	PD average; etc
	Column vector	Average; Covariance; Skewness; Kurtosis; etc		
PD occurrence matrix	Row vector	Average; Covariance; Skewness; Kurtosis; etc	Entropy; etc	PD average; etc
	Column vector	Average; Covariance; Skewness; Kurtosis; etc		

2.4 Diagnosis

Supervised learning in neural network for PD pattern recognition was performed based on the PD pattern database which was established by laboratory test and on-site PD detection. As a result of learning process, the best weights and bias are finally stored.

In diagnosis stage, the obtained weights and bias are applied to PD data and diagnosis results are given through internal matrix computation.

2.5 Final decision

In final decision stage, the highest value among the PD diagnosis results is chosen as the first PD source, and the value is recalculated in percent (%) and displayed.

3 DIAGNOSTIC ALGORITHM

In this study, neural network combined with genetic algorithm was employed.

3.1 Neural network algorithm

Multilayer perceptrons which are feedforward neural networks trained with the standard backpropagation algorithm were modelled. The cross-validation (early stopping) was also used to detect and prevent overtraining (or overfitting) [3].

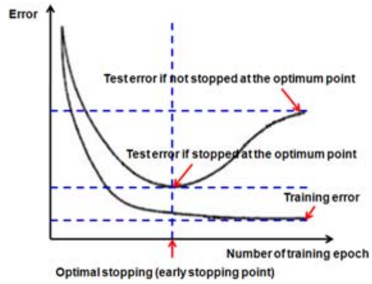

Figure 6: Cross validation (early stopping)

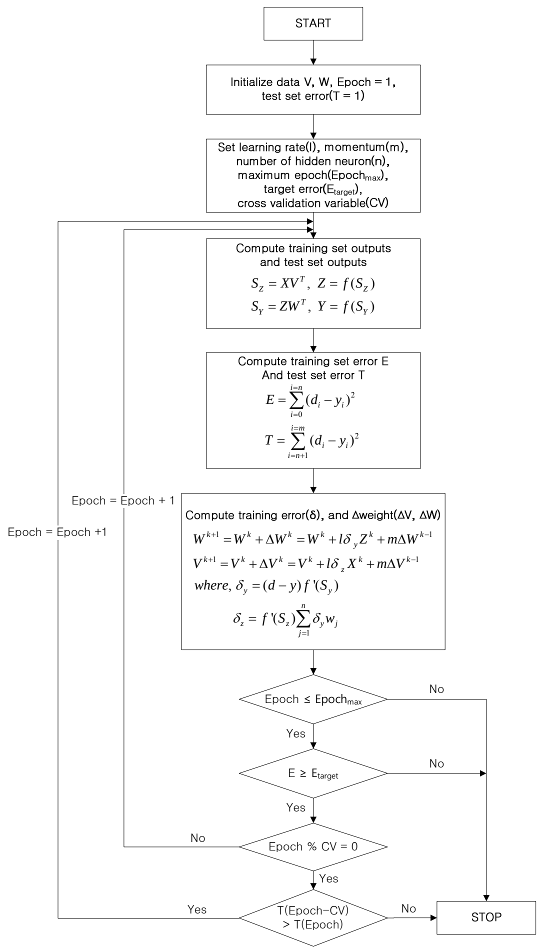

Figure 7: Flow chart of neural network algorithm with cross validation

3.2 Genetic algorithm

In order to improve the PD pattern recognition rate, the number of neurons of hidden layer, learning rate, and momentum were optimized by genetic algorithm as shown in Table 2 [4].

Table 2: Genetic algorithm

Step 1. /Initialize momentum(m), learning rate(l) and the number of neurons of hidden layer(n) randomly/

$r \leftarrow 0$;

initialize m^0 , l^0 , and n^0 ;

Step 2. /Evaluate MSE of MLP/

Fit[0] $\leftarrow$ Update_Parameter(m^0 , l^0 , n^0);

Step 3. /Reproduce new population with crossover and mutation/

{ m^r , l^r , n^r } $\leftarrow$ **Select( )**; /Select fit pair of parent NN parameters/

{ m^r , l^r , n^r } $\leftarrow$ **Crossover( )**; /Pick random position and do crossovers/

{ m^r , l^r , n^r } $\leftarrow$ **Mutate( )**; /Mutate both new chromosomes at random/

Step 4. /Evaluate fitness/

Fit[r] $\leftarrow$ Update_Parameter{ m^r , l^r , n^r }; /Replace population/

Step 5. /Test stopping criterion/

$r \leftarrow r+1$;

if $r \le l$, then goto Step 3; /Iterate again, or else/

else **Get_solution( )**; /Get best solution from population/

stop;

The PD diagnostic algorithm training program was implemented by using the developed neural network combined with genetic algorithm.

Figure 8: PD diagnostic algorithm training program

3.3 PD diagnostic algorithm

The optimized neural network by the program was adopted in PD diagnostic algorithm. This algorithm decides PD defect through the internal matrix computation.

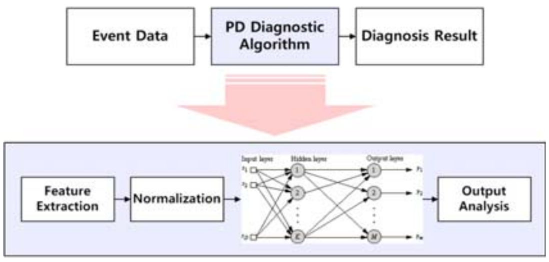

Figure 9: PD diagnostic algorithm

4 ON-SITE VERIFICATION

The PD diagnostic algorithm was applied to on-site 170kV three-phase GIS in which PD had occurred. Although the phase of detected PD pattern was shifted, the diagnosis result coincided with the PD source. It can be shown that the newly developed algorithm is proven to be appropriate for PD diagnosis without any phase information.

Figure 10: On-site PD detection system

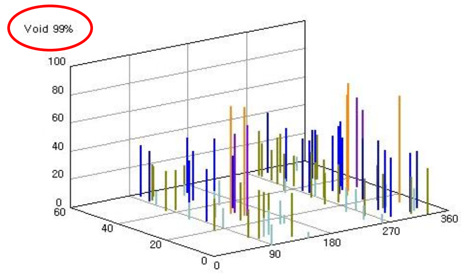

Figure 11: Detected PD pattern & diagnosis result

5 CONCLUSION

In this study, the PD diagnostic algorithm for single-phase GIS and three-phase GIS was described. Important remarks could be deduced as follows:

- The histogram preprocessing and the phase-independent feature extraction were suggested for PD pattern recognition.
- The pattern recognition program was implemented based on neural network with genetic algorithm.
- The novel PD diagnostic algorithm was developed by using above mentioned techniques.
- The validation of the algorithm was verified through the on-site test.

6 REFERENCES

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