Diagnosis System for Insulation Degradation Based on 2D Pattern Data

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Abstract: - This paper proposes a new method for the diagnosis of insulation aging. The proposed system measures the partial discharge acquired on-line from a Data Acquisition System (DAS) and acquires two-dimensional (2D) patterns from wavelet analysis. Using this data, the design for a Neuro-Fuzzy Model (NFM) that diagnoses insulation degradation in electrical equipment is developed. The system is implemented in a prototype system and its validity is evaluated by numerical analysis and simulation.

Key-Words: - Diagnosis system, Neuro-Fuzzy Model, Data Acquisition system, Neural Network

1 Introduction

Dependable equipment performance and operation is an important factor in the reliability of industrial facilities. This is largely due to the steadily increasing use of larger and more powerful Flexible Assembly (FA) and Computer Integrated Manufacturing (CIM) systems in industrial production and manufacturing. As these machines become more autonomous, insulation breakage, due to overloading and insulation degradation in high voltage electrical equipment, such as Potential Transformers (PT) and Current Transformers (CT), can cause serious production and safety risks in autonomous systems. Insulation degradation is caused by an unbalanced distribution of electrical fields and the existence of internal insulation material voids that originate from poor insulation production and molding technology. As an insulating material degrades, the electrical and mechanical characteristics of the system become unpredictable, often resulting in serious and costly failures and safety hazards. Partial discharge across an insulating material is directly related to insulation degradation and the main cause of failure in the high voltage electrical equipment.

It has been found that persistent observation of partial discharge is an effective method for insulation degradation diagnosis to reduce and avoid insulation failures. Detection methods for partial discharges in electrical equipment, such as the detection of an electrical current pulse produced by a partial discharge using a Rogowski coil, measurement of electromagnetic waves, and detection of ultrasonic waves by equipment probes in a transformer box, have been studied [5, 6, 8, 9], but it is difficult to get reliable data from these methods because of the electromagnetic and ultrasonic wave noise in this complex environment. Even when it is possible to perform practical observations of the partial discharge, it is difficult to define a standard for the insulation degradation process, classify the degradation status and diagnose the system, due to the system's electrical and mechanical complexity. Recently the 3D pattern of partial discharges, utilizing phase, magnitude and count characteristics, has been used to evaluate the relationship between partial discharges and the insulation degradation status, but accurate diagnosis needs to apply expert knowledge for proper performance. In order to develop this type of knowledge integration, the parameters for an automatic recognition inference system must be investigated and their interrelationship identified.

The study of diagnostic systems for insulation degradation has concentrated on the investigation of a new analysis method in partial discharges and the application of this method to develop a practical diagnosis system [2, 4, 5, 6, 7 10, 11]. These methods have exhibited difficulties in field testing since the dynamic characteristics of insulation degradation are highly nonlinear and not easily modeled. Furthermore, these methods require complex, expensive and high precision hardware. To address this issue, this paper proposes a neuro-fuzzy diagnostic model to diagnose insulation degradation using 2D patterns of the count and magnitude of partial discharges from phase invariant periodic data and compares it to the 3D patterns developed in existing quantitative methods.

2 Partial Discharge Analysis

Partial discharge is the electrical phenomenon where current leaks outside of a closed circuit through insulating materials. This results in the progressive degradation and breakdown of insulation. The categories of the phenomenon are internal discharge, surface discharge, corona discharge, electrical tree discharge and discharge through a material with low insulation strength. It generally occurs in the insulation cavities containing gas or oil. The breakdown point of an insulator is determined by the position, cavity shape and the type and pressure of the cavity gas or oil. Additional cavity materials that induce low voltage discharge include dust, paper, fabric and other materials.

Fig. 1 shows the mechanics of a partial discharge from an AC voltage source. In Fig.1, 'a' denotes the branching electric charge through leaking insulation, 'b' denotes the electric current through the insulator connected to a cavity and 'c' corresponds to the properly operating part of the insulator. If a voltage is applied to the circuit, 'c' charges to the maximum and the insulation has allowed a discharge. This charge and discharge process is cyclically repeated.

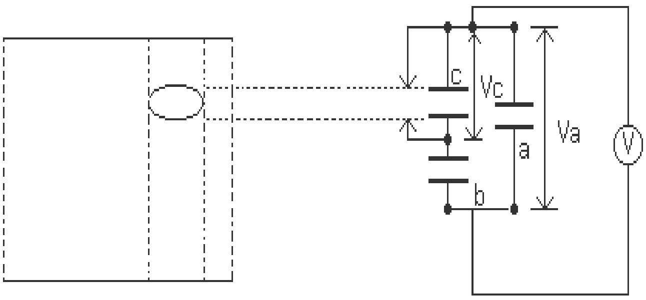

Fig.1. a-b-c Circuit

In Fig. 2, Va and Vc are the voltages applied to the insulator and cavity, respectively. When Vc approaches the insulation breakage voltage U+, breakage occurs in the cavity. After discharging, the voltage drops to the remaining voltage V+. Here U+ is also called the discharge igniting voltage and given by a Paschen curve for the cavity gas. Partial discharge accompanies physical phenomena such as current, electromagnetic and ultrasonic waves and light. These physical variables can be measured and

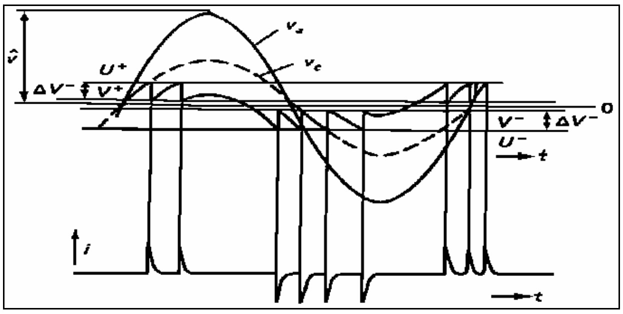

Fig. 2. Generation of Partial Discharge

utilized in the analysis of the dynamic characteristics of partial discharges. The current wave generated by a partial discharge is measured and utilized in the analysis of the dynamic characteristics of partial discharge and the correlation between partial discharges and insulation degradation is exploited. Insulation degradation may then be diagnosed from these characteristics.

2.1 Wavelet Transformation (WT)

A wavelet is defined as the signal whose average is effectively zeroed in a finite period. Wavelet analysis recursively decomposes the original signal using the root wavelet transition value and variant scale value. It is an effective method to detect instant signal change, because the signal trend in multiple frequency components can be measured in a real time manner. Traditional Fourier Transform (FT) decomposes the signal into sinusoidal waves with different frequencies and differs from Wavelet Transformation (WT). FT analyzes the signal in time for the whole range (time-Volt) into a frequency spectrum (frequency-magnitude). FT has difficulty in analyzing continuous frequency components. Although Short-Time Fourier Transform (STFT) can be applied to solve this problem, WT is more effective for real time signal analysis [1,2]. WT also has the property of filtering out noise, thereby minimizing the effect of noise and providing the proper characteristics for nonlinear system analysis [3, 4]. WT has a continuous or discrete parameter scale value and a shift or position index. Continuous WT (CWT) in the square integral Hilbert space is:

$$CWT_X(\tau, a) = \frac{1}{\sqrt{|a|}} \int f(t) \varphi^* \left(\frac{t-\tau}{a} \right) dt \quad (1)$$

Here,

$$\varphi_{ab} = \frac{\varphi\left(\frac{(t-b)}{a} \right)}{a} \quad (2)$$

$$\varphi(t) = \Phi(t)e^{(-2\pi f_0 t)} and, \quad a = \frac{f_0}{f} \qquad (3)$$

where a is the real scale index, τ is the shift index and and Φ(t) denotes the scaling function.

Fig. 3 shows results of CWT analysis represented by the variables time, scale and coefficient using the Matlab 5.0 GUI tool. A small scale corresponds to a high-speed signal and large scale to a low speed signal. Thus, adaptive real time signal processing is possible and each coefficient changes according to the scale value. This coefficient corresponds to original signal's frequency component.

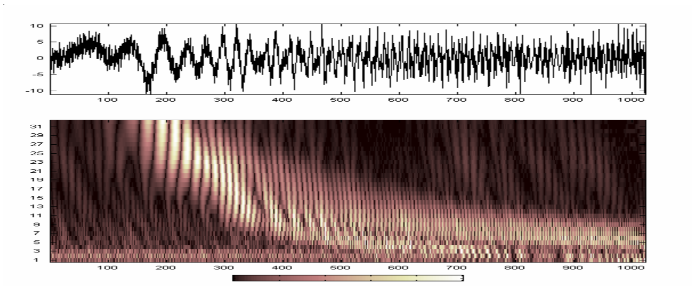

Fig. 3. Signal by CWT analysis

A discrete WT (DWT) has the following definition:

$$DWT\,(a,\tau) = \sum_{n \in Z} f(n)\Phi_{a,\tau}(n) \qquad (4)$$

$$\Phi_{(a,\tau)}(n) = 2^{-\frac{a}{2}}\Phi(2^{-a}n - \tau) \qquad (5)$$

Here, Φ (t) is the primary function, a is the scale index and τ is location index. The scale index denotes the width of WT and the location index denotes the position of the WT. W(t) is a scaling function as follows:

$$W(t) = \sum_{k=1}^{N-2}(-1)^k c_{k+1}\Phi(2t + k) \qquad (6)$$

Here, c is coefficient of WT. Coefficients should satisfy the following condition:

$$\sum_{k=0}^{N-1} c_k = 2, \sum_{k=0}^{N-1} c_k c_l = 2\delta_{l,0} \qquad (7)$$

Here, delta is Kronecker's delta function. In a DWT, a scale value can be varied in the finite range. A large value can classify low frequency components and a small value can classify high frequency components. Large and small-scale values have coefficients, called approximations and details, respectively. In Fig. 4, decomposition is shown with the multiple level components according to scale values. For optimal signal processing, the selection of optimal coefficients is performed using various measurement functions or the neural network's learning ability. Optimal levels for tree structures can be obtained [4, 5].

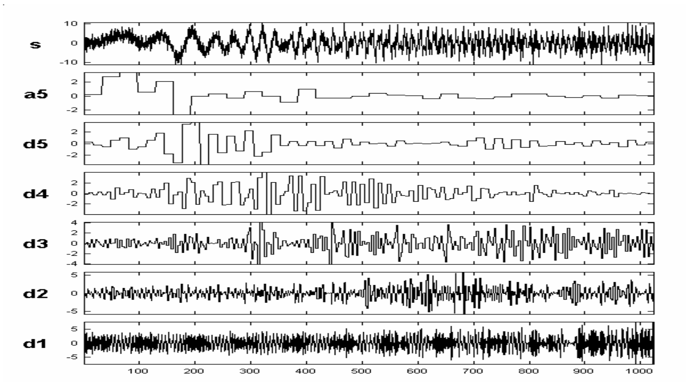

Fig. 4. Signal analysis using 1-D DWT

In this paper, noise contained in the current wave measurement signal is removed using wavelets. From the filtered signal, a 2D pattern data of insulation degradation is obtained by counting the impulse wave of current above the threshold magnitude.

3 Design of the Diagnosis Model

In this study, the diagnosis model uses the neuro-fuzzy model, which is suitable for noise and nonlinear properties. Conventional neural network models are complex and difficult to understand. Robustness is a merit of neural networks. A more robust model is desirable for the proper processing of noisy signals, since the signal generated by discharge is so fine. An inference system based on the neuro-fuzzy model and pattern recognition method using wavelets is adapted for this application.

3.1 Discharge Measuring System

The partial discharge measuring system depicted in Fig. 5 consists of a Rogowski coil to sense the current wave, a filter for noise reduction, and other parts for data acquisition, as required by the data acquisition system. A stable high voltage power source is applied and the sampling frequency is 10Khz. The current wave generated by the partial discharge is measured. Data is continuously acquired for 12 cycles per group. The acquired signal is a random signal in the range of 0 to 3 and contains noise. After filtering out the noise using wavelets, the resulting signal has a low frequency of about 60Hz. Analysis of the signal using wavelet is done with the maximum impulse signal and signal normalization to correlate the partial discharge with

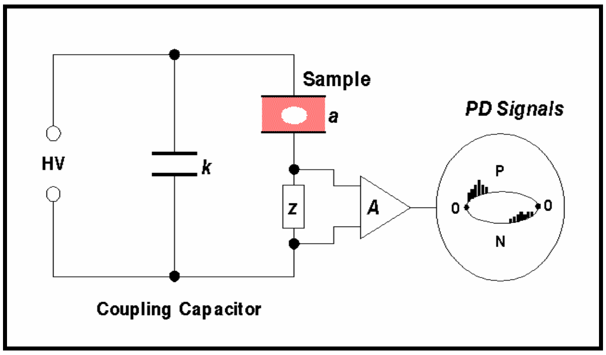

Fig. 5. Block Diagram of Partial

insulation degradation. This makes it possible to organize the inference system evaluating degradation status from an unknown signal. The current wave of a partial discharge, as shown Figure 6 (d3), is an unexpected discrete impulse wave. This wave has information about partial discharges above the size limit. By applying the feature extraction process using wavelets, 2 dimensional input data is acquired as the count per second and scale value. Discrete data is acquired across the discharge and breakdown process for a uniform interval.

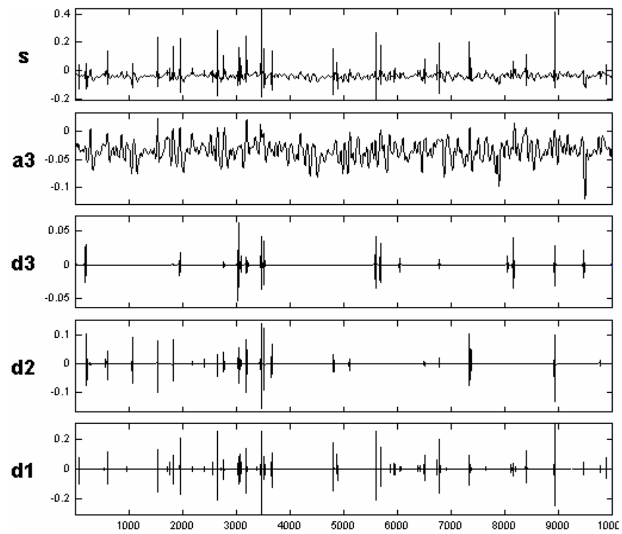

Fig. 6. Source and Analyzed Signals

3.2 Design of the Diagnosis Model

For i-th input variables xn (n=1, 2) and the output variable yi, the fuzzy production rule is represented as follows:

$$R^i : \text{if } x_1 \text{ is } A_1^i \text{ and } x_2 \text{ is } A_2^i, \text{then } y^i = b^i, \ (i=1,2,3,\ldots,c) \quad (8)$$

Here R^i is i-th rule, c is number of rules, A_1, A_2 are triangular fuzzy sets, y^i is i-th consequent and b^i is i-th singleton output. The max-product composite fuzzy inference method is applied for input data (x_1, x_2) and crisp, defuzzified model output is computed by:

$$w^i = \mu_{A1}^i(x_1) \times \mu_{A2}^i(x_2) \quad (9)$$

$$y = \frac{\sum_{i=0}^{m} w^i \times y^i}{\sum_{i=0}^{m} w^i} \quad (10)$$

Here,, $\mu_{A1}^i(x_1)$ is the membership function for the fuzzy set A_1, $\mu_{A2}^i(x_2)$ is membership function for fuzzy set A_2, y^i is i-th output, w^i, w^i is compatibility of input (x_1, x_2) to rule R^i. As shown in Figure 7, the membership function for input to the

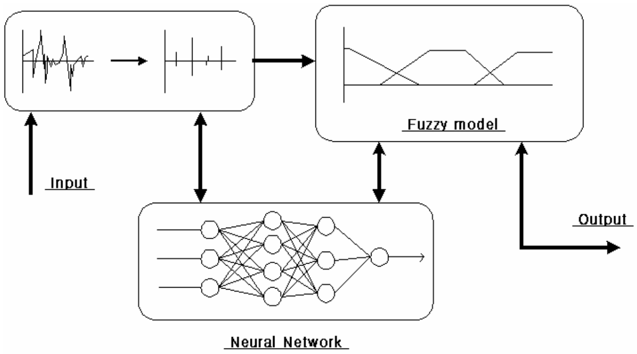

Fig. 7. Neuro-Fuzzy Diagnosis Model

fuzzy set uses a triangular membership function. The rule consists of membership function values of the input variables. Rule fine-tuning uses back propagation to adjust the fuzzy variable and singleton value in the fuzzy rules using a generalized delta rule.

4 Experimental Results

The current wave from the partial discharge experiments has 10000 sample values per group, as shown in Table 1 After applying the voltage, from the initial partial discharge to final insulation breakage, data consist of 19 groups. The value s, in Figure 6, is the composite signal obtained through the noise reduction process using wavelets. Results indicate that the high frequency component is mixed over a primary low frequency component at 60Hz. The finite pulse current is shown at phase angles of 90°and 270°. In this experiment, noise is removed using wavelet for negative phase. Using the wavelet filter function, the partial discharge occurrence count above the threshold, or lower bound of the magnitude, and the high frequency component, d3 (Decamp/ 3 level), are obtained, as shown in Figure

6. The occurrence count and the integral value of the pulse signal of a partial discharge become attributes of feature pattern, as shown in Table 1. This depicts

Table 1

Groups	Count	Scale
1	0(0)	-7.8099e+003, -7.8113e+003
2	0(0)	-8.6136e+003, -8.6140e+003
3	11(3)	-3.2890e+003,-3.2894e+003
4	13(3)	-883.3157,-883.5000
5	17(2)	-296.3443,-342.1870
6	18(2)	-344.7555,-339.4140
7	12(1)	-359.0311,-322.1813
8	18(2)	-261.4078,-292.6427
9	18(0)	-288.0817,-267.3261
10	20(0)	-158.4500,-206.5498
11	27(6)	-186.8032,-175.7643
12	22(10)	79.5891,78.4305
13	24(19)	255.5805,254.5124
14	24(24)	552.6942,551.3547
15	24(24)	592.5400,567.6947
16	24(24)	496.9675,579.3758
17	24(24)	581.9201,588.6491
18	24(24)	761.0831,763.3684
19	24(24)	773.7059,772.8384

that nonlinear characteristics do not provide a smooth pattern. It also reveals the complex relationship between insulation degradation and partial discharge.

Figure 8 shows that inference from the diagnosis system is better than the actual measurement for the estimation of the progress of insulation degradation. This research suggests the applicability of a diagnosis system based on the 2D pattern, using the magnitude and count of the current wave signal of partial discharge and preprocessed by a wavelet filter and its improvement over 3D analysis. Therefore, a more practical diagnosis system, that overcomes the high cost and complexity of phase measurement in previous methods, is realized.

4 Conclusion

In the field of high voltage electrical systems, it is difficult to reliably manage the status of insulation degradation. There are many problems in applying conventional methods that require off line testing where power is shut down, production lines are halted and measuring devices must be installed in

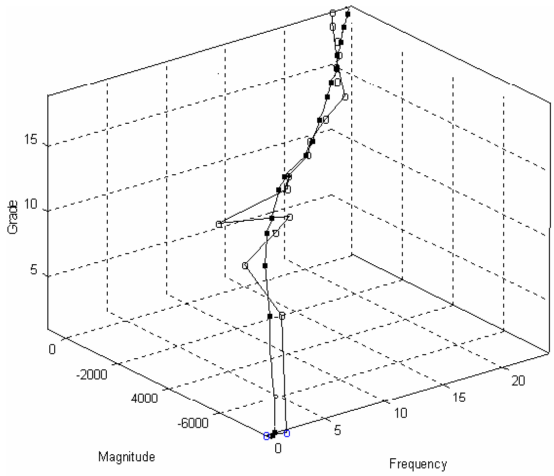

Fig. 8 The Result of Proposed Diagnosis System
(*: Reasoning data, 0:Real data)

the proper positions. In the previous methods, these system configurations to measure the many variables are complex and expensive. While some research studies have found solutions to these problems, using 3D, frequency-analyzing and fractal based tree analyzing methods, these methods exhibit problems. A phase variable measurement, where, partial discharge is discontinuous in time and the range of frequency (2MHz-40MHz) is too broad to measure reliably, requires a complex and high cost system. To solve these problems, this research proposed a diagnosis system based on 2D pattern data and the experimental results show its improved performance and usefulness. Further study is necessary to overcome the discontinuous nature of partial discharge signals and to produce general reference patterns for diverse environments. Further study that combines the result of this research with the method using electromagnetic wave should provide more practical systems for commercial purpose.

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