Data Analysis Using Hilbert-Huang Transform for Partial Discharge in Low Voltage Motors

Ya-Wen Tang, *Student Member, IEEE*, Cheng-Chi Tai, *Senior Member, IEEE*, and Ching-Chau Su

Abstract — **Over the course of the past 20 years, the number of signal processing methods used to analyze the partial discharge (PD) of electrical equipments has greatly increased. In this paper, we analyze and compare the PD signals from acoustic emission (AE) and high-frequency current transformer (HFCT) measurements with Hilbert-Huang Transform~~s~~ (HHT). The HHT demonstrates several excellent advantages in the PD signal analysis application.**

Index Terms—**Partial discharge (PD), Acoustic emission (AE), Hilbert-Huang Transform (HHT)**

I. Introduction

As modern economies and populations grow rapidly, power conservation is even more important. Most low voltage motors operate with the PWM technique, but the isolation is not enough for the rated frequency. During high voltage switching, the transient voltage greatly exceeds the maximum tolerance which is anticipated to be isolated [1]. These motors operated in such situation for a long period would result in partial discharges (PD). The partial discharge increase the users' risk of unexpected short circuit, electric leakage, or ablaze.

The commonly used methods for motor PD detection are the couple capacitance method and the electrical method. Both methods are used for high capacity motors operated with median or high voltage. In order to distinguish between the PD signal and noise, the sampling rate of these methods should be higher than the frequency response of sensor output. This means that the requisite hardware is too expensive for use with low voltage motors. Recently an acoustic emission (AE) method has been presented for low-cost PD detection in cast-resin dry-type transformer [2]. In this work, the acoustic emission method and electrical method were used for PD data collection.

Several systems have used intelligent systems techniques, such as Artificial Neural Network (ANN) [3], to recognize different PD signals. But the main concern of this research is focused on the frequency and amplitude variations around the PD occurrence. Therefore, signal processing methods such as Fourier Transformation and Hilbert-Huang Transformation (HHT) are applied to analyze the PD signal.

The Fourier Transformation is often used for PD signal analysis. The Fourier Transformation provides the detail information at frequency response. However, when the Fourier Transformation is applied to irregular signals, such as PD signals, the energy spectra are invariant with respect to time shifts. Therefore the Fourier Transformation is not sufficient for detecting the instant when PD occurs. This paper proposes the HHT method to analysis the PD signal in the case of low-voltage motor. HHT is a novel analytic method for time-frequency domains. It helps us discern the relationship between the time and frequency of the PD occurrence.

II. Measurements Methods

The electrical method and AE method used to detect the partial discharge signal will be introduced sequentially.

A. Electrical Method

The electrical method is a common method for on-line PD detection. A high frequency current transformer (HFCT) is used to sense PD signals from the ground lead. When partial discharge occurs, considerable current will flow through the ground lead. The HFCT sensor will then induce a pulse current variation from the ground lead. The power instruments which are well grounded for safety make it possible to measure the PD signal from the ground lead. The electrical method has been used to confirm the occurrence of PD signals in a low voltage motor.

B. AE Method

The AE method is a non-electrical method for PD detection. The partial discharge results in a pressure wave which collides with the inner elements and neighboring elements of the motor equipment. The center of the collision forms an acoustic emission source, and communicates the wave all over. Since the PD signal comes in the form of an acoustic emission, an acoustic sensor can be placed close to the surface of the motor.

A block diagram of this measuring system is shown in Fig. 1. The target motor is a three-phase driven induction motor. In order to measure the partial discharge signal, a generator and a three-phase resistor were connected to the target motor. AE signals and HFCT signals were used to confirm the presence of PD in this device. The AE sensors with a 150 kHz frequency response were placed near the motor casing and the HFCT sensor was installed to the ground lead. Both the sensor

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outputs are amplified with a single stage amplifier, and recorded by a digital oscilloscope (LeCory LT354).

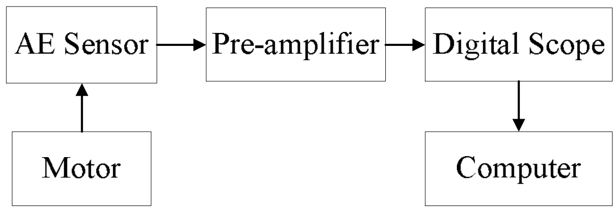

Fig. 1. PD measurement system for an active motor.

The acoustic signal transferred to the AE sensor is direct coupled from the target. Since the resonant frequency of the sensor is much lower than the electromagnetic (EM) interferences around the motor, the effects of noise is substantially reduced by this method. In the mean time, the using of 150-kHz resonant type AE sensor also avoids the disturbance of mechanical vibration.

III. Signal Analysis

A. HHT analytical Method

The HHT is a signal analysis method that combines the empirical mode decomposition (EMD) and the Hilbert spectral analysis (HSA) [4]. The first step uses the EMD process to deconstruct the data into several intrinsic mode function (IMF) components as follows: (1) identifies all the local maxima and connects them by a cubic spline line to serve as the upper envelope. (2) Repeat this process for the local minima to produce the lower envelope. The upper and lower envelopes should cover all the data between them. (3) The data series *X(t)* is first decomposed into a finite number n intrinsic mode functions C_j, with the extracted energy associated with various intrinsic time scales and residual r_n.

$$X(t) = \sum_{j=1}^{n} C_j(t) + r_n(t) \tag{1}$$

These IMFs are expanded on a basis derived from the data itself. The IMF comply with the following two conditions: (1) in the whole dataset, the number of extrema and the number of zero crossings must either be equal or differ at most by one; and (2) at any point, the mean value between the envelope defined by the local maxima and the envelope defined by the local minima is zero.

In the second step, Hilbert spectral analysis is applied to the following IMFs:

$$\hat{C}_j(t) = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{C_j(t')}{t - t'} dt' \tag{2}$$

where P indicates the Cauchy principal value.

The amplitude a_j, the phase φ_j and the instantaneous frequency ω_j are calculated by

$$a_j(t) = \sqrt{C_j^2(t) + \hat{C}_j^2(t)} \tag{3}$$

$$\varphi_j(t) = arctg\left(\frac{\hat{C}(t)}{C(t)}\right) \tag{4}$$

$$\omega_j(t) = \frac{d\,\varphi_j(t)}{dt} \tag{5}$$

Using (3)-(5), the original data *X (t)* can be expressed as a real part (Re) of the complex expansion:

$$X(t) = \mathrm{Re} \sum_{j=1}^{n} a_j(t) e^{i\int \omega_j(t)dt} \tag{6}$$

which is considered to be a generalized from of the Fourier expansion with time variable amplitudes and frequencies.

The time-frequency distribution of the amplitude designated as a Hilbert amplitude spectrum and determined as a time-frequency distribution of the amplitude, is utilized. For simplicity, the Hilbert energy spectrum is denoted as Hilbert spectrum $H(\omega, t)$.

The Hilbert energy spectrum preserved the time localities of events; the frequency and energy defined by the Hilbert transform expressed the intrinsic physical meaning at any point. The time location provide the important information that is impossible to be seen in FFT analytical Method.

From the Hilbert spectrum $H(\omega, t)$, the marginal spectrum $h(\omega)$ can be determined as:

$$h(\omega) = \int_0^T H(\omega, t) dt \tag{7}$$

where T is a total data length. The marginal spectrum offers a measure of the total energy contribution from each frequency value. It represents the accumulated energy over the entire data span. In this work, the marginal spectrum is used to display the power variation with regard to the frequency.

IV. Results And Discussion

The PD signal was acquired from the measurement system, as shown in Fig. 1. All data were recorded with a 100 MHz sampling rate by the oscilloscope, and stored in a file in binary format. All the data shown in this paper were analyzed off-line with the MATLAB™ software package. The calculated AE and HFCT signals are shown in Figs. 2 and 3, respectively. The datasets used span the entire breadth of the data acquisition time. There is a PD occurrence in the HFCT signal at 0.05 msec. The same PD occurrence is detected in the AE signal at 0.39 msec. Because of the time differential between an electromagnetic wave and an acoustic wave, the PD occurrence time in HFCT signals should have a lead of 0.34 msec.

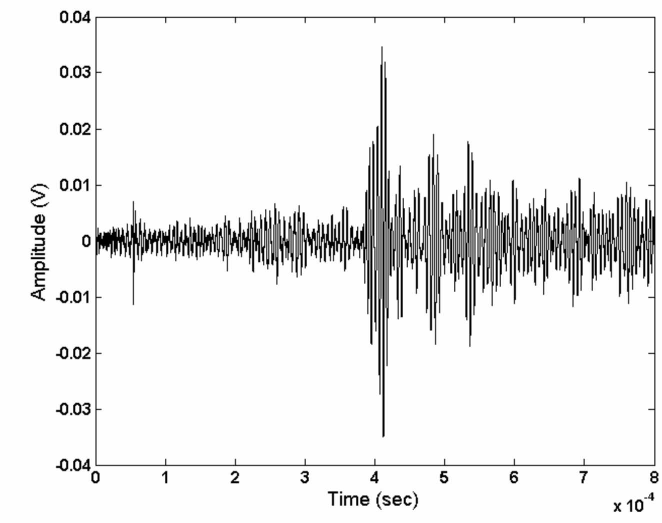

Fig. 2. The original PD signal from AE measurement.

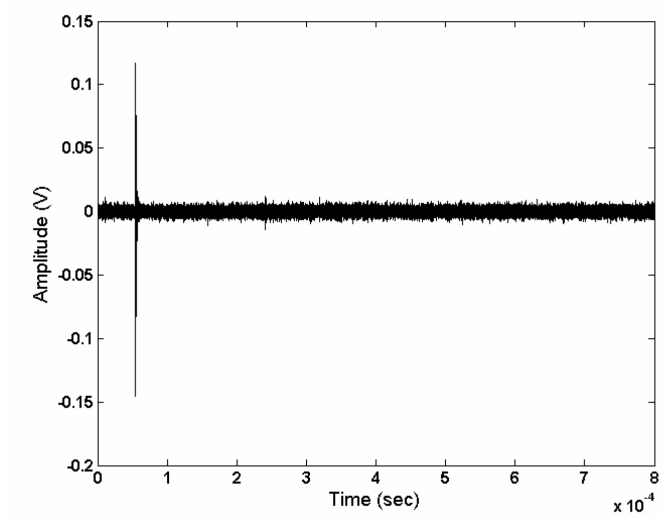

Fig. 3. The original PD signal from HFCT measurement.

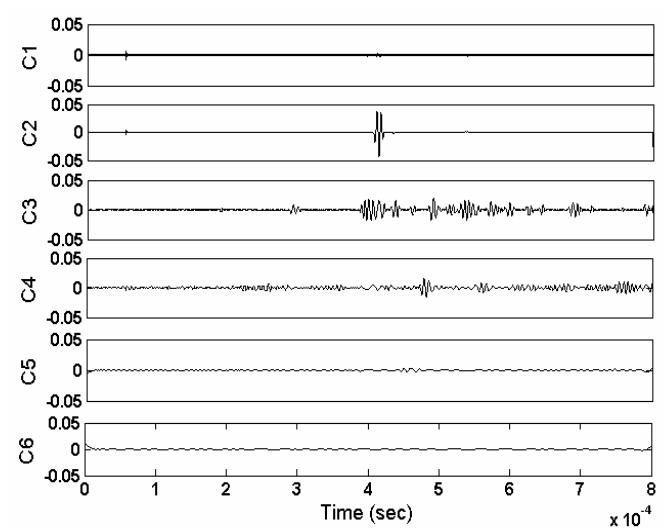

Fig. 4. Intrinsic mode function (IMF) components derived from the AE data by the empirical-mode decomposing method.

First, the EMD method was applied both to the AE signal and HFCT signal, and the results are shown in Figs. 4 and 5 respectively. As shown in Fig. 4, the AE signal has six intrinsic mode functions. As shown in Fig. 5, the HFCT signal reveals seven intrinsic mode functions. Whether the IMF is in AE signal or in HFCT signal, the first IMF exhibits the higher frequency, and stronger power; the last IMF displays the slower frequency, and weaker power.

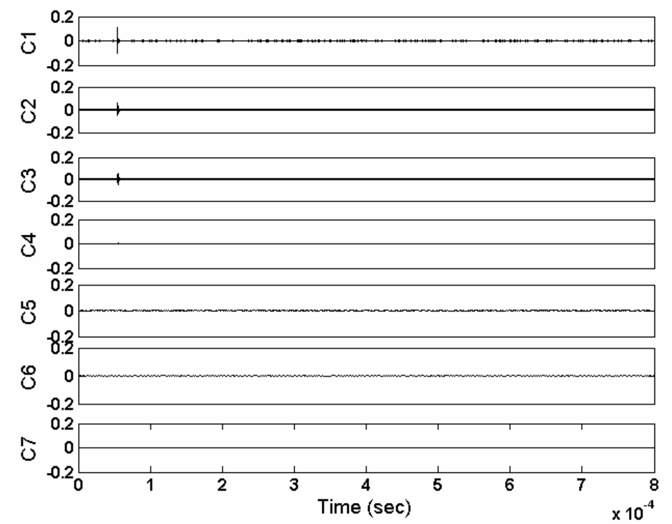

Fig. 5. Intrinsic mode function (IMF) components derived from the HFCT data by the empirical-mode decomposing method.

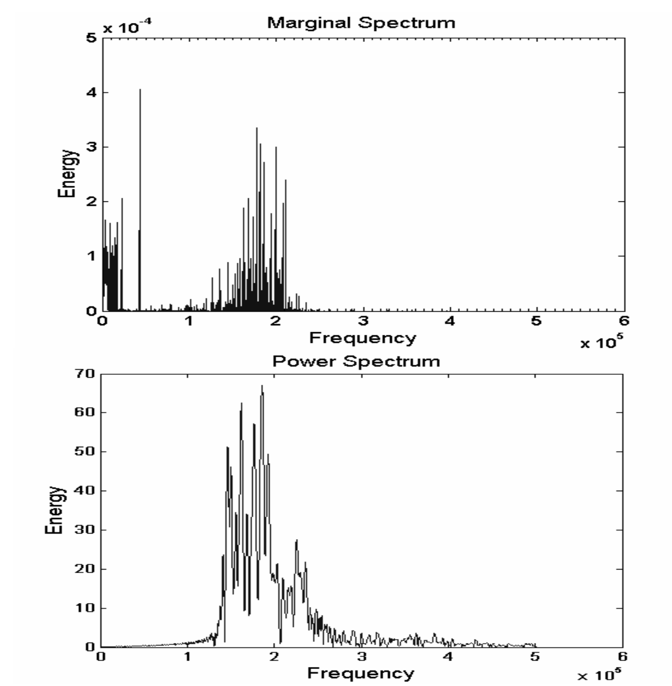

Fig. 6. Hilbert marginal spectrum and FFT power spectrum of AE data.

After the EMD method, the Hilbert Marginal Spectrum and Fast Fourier Transformation (FFT) methods are applied to the AE signal and HFCT signal, and the results are shown in Figs. 6 and 7 respectively. The peak frequency of the AE signal is 178 kHz and the peak frequency of the HFCT signal is 2.65 MHz in the HHT marginal spectrum. The peak frequency of the AE signal is 186 kHz, and the peak frequency of the HFCT signal is 12.5 MHz in the FFT power spectrum. The accuracy of HHT method is confirmed by comparing it to the results obtained with the FFT method. The peak frequency of HFCT signal using the FFT method obviously is a misjudgment. There are several components below the peak frequency in Figs. 6 and 7. The sources of low frequency bands may be electric inference from ambient electric switches.

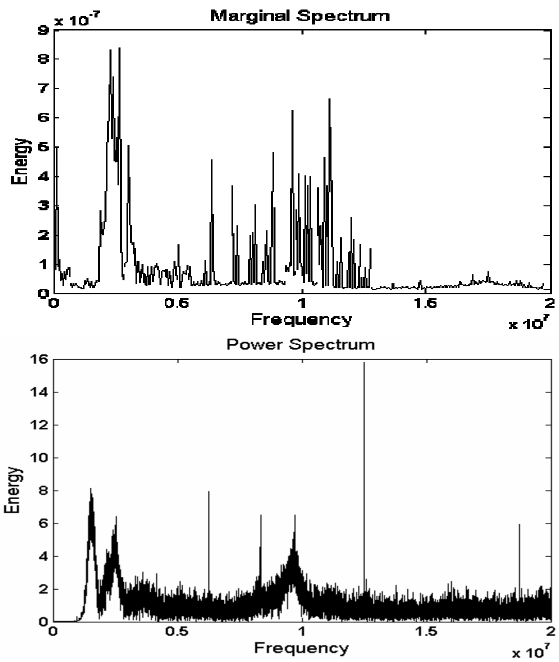

Fig. 7. Hilbert marginal spectrum and FFT power spectrum of HFCT data.

The HHT results in Figs. 6 and 7 show the differences to the traditional frequency method. The HHT illustrates the explicit relationship between time and frequency around the PD occurrence. Furthermore HHT provides strong inferences in the low frequency band. Possible sources of this come from the transient response of the environment. The noise coming from the ground line affects HFCT signals serially and covers the PD signal. When compared to the HHT results, some components of the PD signal are lost. An explanation for this may lie in the fact that the FFT algorithm is based on a linear and stationary dataset while the PD signals are nonlinear and non-stationary in nature. Therefore, when the FFT is applied to PD signal analysis, it presents a serious limitation. It can not provide the relationship between the time and frequency in which transient phenomena occur.

V. Conclusion

PD signal analysis is critically important to the operation safety of motors. The AE method and HFCT methods provide ways to detect the PD signal of an active motor. The low cost make AE method possible to be applied to low-voltage motor PD detection. HHT method is an appropriate technique for PD signal analysis. The AE sensor with HHT algorithm can be used to inspect PD signal for long-term monitoring.

Traditionally, the method of FFT is used to illustrate information in frequency domain. As can be found from Figs. 6 and 7, the main frequency components of PD signals are 186.1 kHz and 12.5 MHz respectively. The nonlinear and non-stationary method, HHT, has been proposed to analyze the PD signals in the low-voltage motor. The HHT, a time-frequency domain method, supplies another viewpoint to interpret the PD signals. This method allows for collecting information on PD signals both with regards to the time and frequency domains simultaneously. This has been found to provide more reliable information when HHT compared with Fourier transformation [5]. The results reported here show that the HHT method has great promise for motor PD signals analysis.

VI. References

[1] D. Bogh, J. Coffee, G. Stone, and J. Custodio, "Partial-discharge-inception testing on low-voltage motors," *IEEE Trans. Industry Applications,* vol. 42, pp. 148-154, 2006.

[2] C.-C. Su, S.-C. Liu, Y.-J. Lin, C.-S. Yi, J.-F. Chen, T.-J. Liang and C.-C. Tai, "Detection of Partial Discharge in Cast-resin Dry-type Transformer by using Acoustic-emission Technique," 16th World Conference on Nondestructive Testing, Montreal, Canada, 2004.

[3] H. Zhang, W.-J. Lee, C. Kwan, Z. Ren, H. Chen, and J. Sheeley, "Artificial neural network based on-line partial discharge monitoring system for motors," Industrial and Commercial Power Systems Technical Conference, pp. 125-132, 2005.

[4] N. E. Huang, M.-L. Wu, W. Qu, S. R. Long, and S. S. P. Shen, "Applications of Hilbert-Huang transform to non-stationary financial time series analysis," *Applied Stochastic Models in Business and Industry,* vol. 19, pp. 245-268, 2003.

[5] X. Wang, B. Li, Z. Liu, H. T. Roman, O. L. Russo, K. K. Chin, and K. R. Farmer, "Analysis of partial discharge signal using the Hilbert-Huang Transform," *IEEE Trans. Power Delivery,* vol. 21, pp. 1063-1067, 2006.

VII. Biographies

Ya-Wen Tang (S'06) was born in Taoyuan, Taiwan R.O.C. She received the M.S. degree in electrical engineering from National Cheng Kung University (NCKU) in 2005, Tainan, Taiwan. She is currently working toward the Ph.D. degree in the nondestructive evaluation (NDE) Laboratory of the Electrical Engineering Department, NCKU. Her research interests include bioelectronic instrumentation, biomedical signal processing and acoustic emission techniques.

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