

Extraction of PD Signals from an Electro-optic Modulator Based PD Measurement System

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Abstract: Partial discharge (PD) measurement is an important technique for assessing the health of power apparatus. Previous published work [1] has shown that an electro-optic system can be used for PD measurement of oil-filled power transformers. The PD signal within an oil-filled power transformer may reach a winding, and then travel along the winding to the bushing core bar. The bushing, acting like a capacitor, can transfer the high frequency components of the partial discharge signal to its tap point. Therefore, an effective PD measurement can be implemented at the bushing tap by using a radio frequency current transducer around the bushing tap earth cable. The use of an optical transmission technique not only improves the noise immunity and provides the possibility of remote measurement but also realizes electrical isolation and enhances the safety for operators. The noise induced by the electro-optic modulator may influence the measurement sensitivity. This paper investigates the use of a machine learning technique to extract the useful PD signals from the noise signals.

Introduction

Partial discharge (PD) measurements are becoming a fundamental approach for quality control and risk assessment of electrical insulation systems. With the development of sensors and measurement techniques, condition based maintenance is attracting more and more interest. Research on continuous online condition monitoring has considered problems, such as remote measurement and transmission, noise immunity, maintenance convenience and operator safety. The use of optical transmission techniques therefore has clear advantages. Work at Southampton has concentrated on implementing an electro-optic modulator (EOM) system to facilitate PD continuous online monitoring of cables [2, 3]. Preliminary research [1] has indicated that the measurement sensitivity may be greatly influenced by optical noise. Research to date has considered using filters, active amplifiers and passive radio frequency systems to improve the sensitivity of the EOM system [1, 4].

The characteristic output signals from the radio frequency current transducer (RFCT) for PD detection within power transformer are different from the signals from the capacitive coupler (CC) for cable PD detection,

not just because the RFCT detects the discharge current as compared to the voltage measurement of the CC but also because it has a lower bandwidth (200MHz compared to 400MHz). It is therefore possible that due to the RFCT's lower signal to noise ratio previous published approaches [1, 4] may be not applicable. It may be possible to amplify the RFCT signal before applying to the electro-optic modulator but this has two disadvantages: Firstly, the active amplifier requires an extra power supply which causes inconvenience in terms of long duration application and will require maintenance. Secondly, the amplifier will also amplify any noise present in the measured signal – given that the bushing will act as an aerial it is likely that any measured signal will contain significant levels of noise.

This paper uses the bushing-tap RFCT system for PD measurement and EOM system for signal transmission as an example and compares the signal extraction performances of a passive band-stop filter and machine learning technique based on different feature parameters. The results obtained from the laboratory based experiment are analyzed and indicate that it is possible to detect discharge signals greater than 30pC.

Experimental arrangement

In this investigation, the PD measurement system comprises a PD detection system and an electro-optic modulator based transmission system.

The PD measurement system

A simple transformer bushing-tap system for PD measurement has been developed and is used as the experimental model, as shown in Figure 1. A connection from the tap point to ground is wound three times around the RFCT. The RFCT has a useful measurement bandwidth of 200MHz. Three turns on the primary side is used to improve the overall measurement gain of the sensor within its bandwidth. This measurement system has been used on-site for on-line PD monitoring of power transformers [5]. The RFCT output signal is fed into the EOM.

A Robinson™ Model 700 conventional PD electrical detector with 40kHz-80kHz band-pass frequency was used to detect and quantify the apparent charge of simulated PD event. A digital oscilloscope,

LeCroy™ LC684DXL with a bandwidth of 1.5GHz, was also used to display, store and analyse the signals from the Robinson™ detector, RFCT and photodiode. The data were also displayed and saved in a personal computer via a GPIB card for further processing.

The simulated PD pulses generated by a LDIC™ LDC-5/RUF UHF calibrator were injected to the bushing core, which can be detected by the Robinson™ detector and RFCT/photoreceiver.

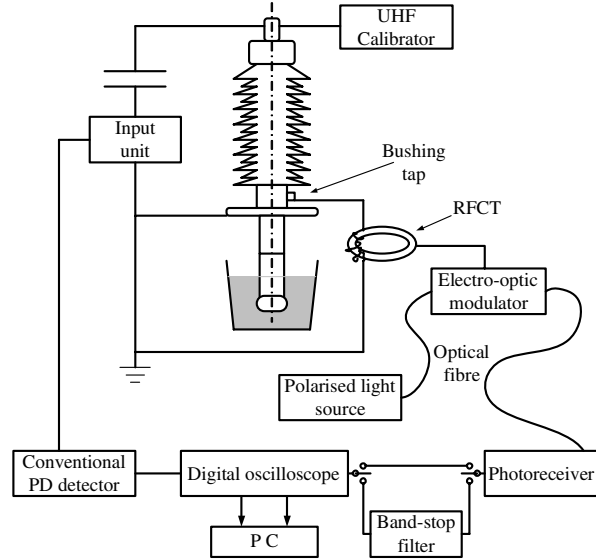


Figure 1: Schematic diagram of the experiment circuit

The electro-optic modulation technique

Figure 2 shows the use of a Lithium Niobate (LiNbO_3) electro-optic modulator. The measurement mechanism uses the measured PD signal and applies it across an optical fiber coupled LiNbO_3 waveguide modulator, which modulates the intensity of the transmitted laser light as an approximately linear function of the voltage applied across it. The optical network supplies polarized laser light via polarization maintaining optical fiber to the LiNbO_3 modulator input, and monitors the optical output from the modulator using an optical receiver. The EO modulator is compact and passive requiring no additional power to operate. The laser source, which is controlled by a temperature and current laser diode controller, has a wavelength of 1550 nm and maximal power of 10 mW. A polarization tuner was used to ensure that the input light for the modulator was linearly polarized. The optical receiver has a bandwidth of 1 GHz.

Figure 3 shows the relationship between a single pulse from a HP™ 8082A pulse generator applied across the EO modulator and the resultant output from the optical receiver. These two signals have similar rise and fall times. The slight delay between two signals is caused by the different transmission path of the

measured pulses and the delay from the EOM system. The injected signal contains frequency components in excess of the useful bandwidth of the RFCT. It can be initially assumed that the method of transmission will not significantly alter the PD signal information.

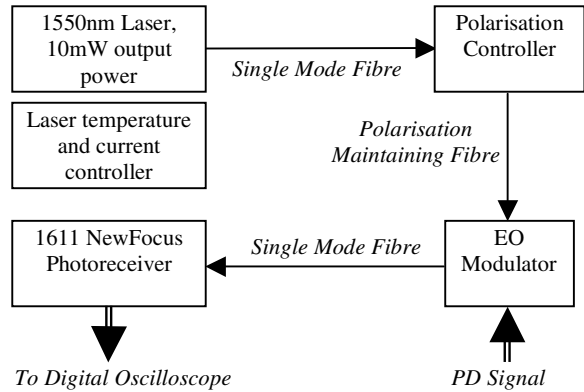


Figure 2: EOM based transmission of PD signal data

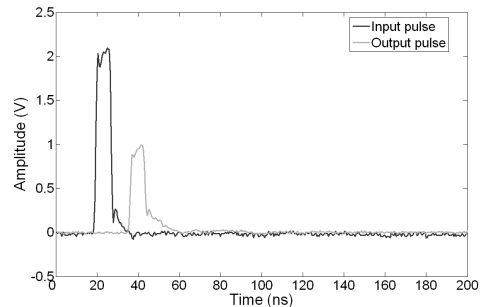


Figure 3: Input of EOM and output of the photoreceiver

Results and discussion

Figure 4 reveals that the background noise level of this EOM system is around 5mV and most frequency components concentrated under 1MHz.

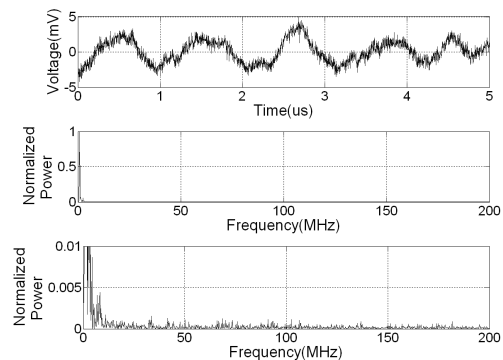


Figure 4: The EOM noise and its frequency spectrum

The minimum detectable PD level of the measurement from the photoreceiver without any filter

or additional data processing is around 160pC, as shown in Figure 5.

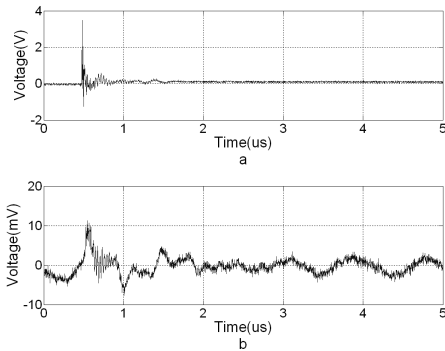


Figure 5: The detectable pulse from the photoreceiver. a. Injected simulated 160 pC PD pulse b. photoreceiver output

Band-stop filter denoising

The characteristic of the background noise from the EOM system makes it possible to apply a band-stop filter to eliminate the frequency component of the noise. A passive filter with band-stop frequency of 540kHz-1.6MHz from Physical and Electronic Laboratories Ltd. was used to depress the background noise. The signal after filtering is shown in Figure 6. The measurement sensitivity is improved to about a 50pC level.

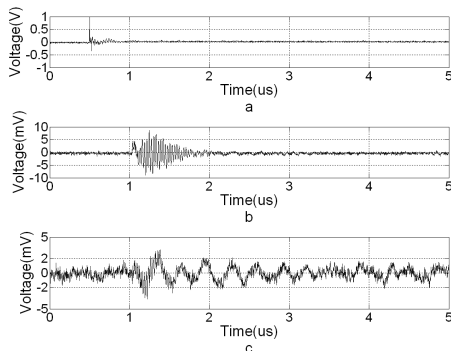


Figure 6: Filter result of a 50pC level signal. a. Injected simulated PD pulse b. RFCT output c. photoreceiver output

Support vector machine identification

As a powerful pattern recognition tool, the support vector machine (SVM) has a solid background: statistical learning theory which has been researched since 1960s. Based on structural risk minimisations (SRM) principles, the SVM was equipped with a greater capability of generalization than traditional neural network approaches. The hyperplane classifier and kernel mapping provide a unifying framework for most of the commonly employed model architectures, enabling comparisons to be performed. In classification problems generalisation control is obtained by maximising the margin, which corresponds to

minimisation of the weight vector in a canonical framework. The solution is obtained as a set of support vectors that can be sparse. These lie on the boundary and as such summarise the information required to separate the data [6]. Relevant research on the application of SVMs can be found in [7, 8].

In this paper, the Gaussian-RBF (Radial Basis Function) kernel,

$$K(x_i, x_j) = \exp\{-\gamma(\|x_i - x_j\|)^2\}. \quad (1)$$

was selected as it has a good performance for this type of application [7]. The frequency spectrum and wavelet decomposition coefficients of the transmitted signal were chosen as the feature parameters respectively.

Due to the bandwidth of the measurement, the sampling rate of the oscilloscope was set to 500MS/s for 5μs. Therefore, there are 2500 points in each acquisition. By segmenting the memory of the oscilloscope, 2800 individual pulses were recorded at each time. The data set which consists of 2800 pulses was also transferred to a personal computer via a GPIB card. Two sets of noise data and eight sets of PD data for 30pC 40pC 50pC 70pC 90pC 110pC 130pC and 160pC apparent charge levels were recorded for processing. As stated in previous section, the minimum detectable PD level without filtering is 160pC. Therefore the SVM was trained with one set of noise data and 160pC PD data and tested with the rest of the data sets.

Frequency spectrum: As the time domain PD pulse and noise are not very separable, some analysis within the frequency domain is worth investigating. Figure 7 shows the frequency spectrum of 160pC PD signal by using the Fast Fourier Transform (FFT).

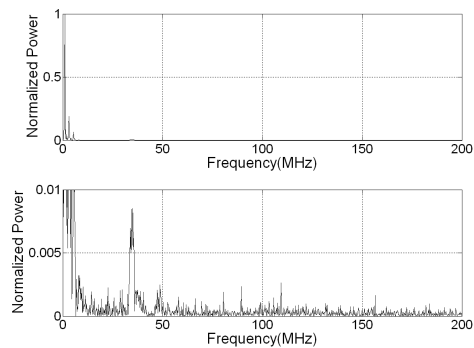


Figure 7: Frequency spectrum of 160pC PD pulse

The FFT results were taken as the input feature for the SVM. However, the identification results are not very satisfying. The training accuracy is 97.875%. At the 130pC level, the identification rate drops down to 67.0714% (1878/2800). This is because the EOM system noise occupies a large number of low frequency components, which greatly affected the ratio to the

comparably lower useful PD frequency components weakening the identification feature.

Wavelet decomposition coefficients: The combination of time domain and frequency domain information provides a better view for us to analyze the signal. Research to date has proposed that the Daubechies family order 7 (db7) may give good results [9]. Therefore in this application, the db7 was chosen as the mother wavelet. Figure 8 shows the decomposition coefficients at seven different levels for noise and 160pC data respectively.

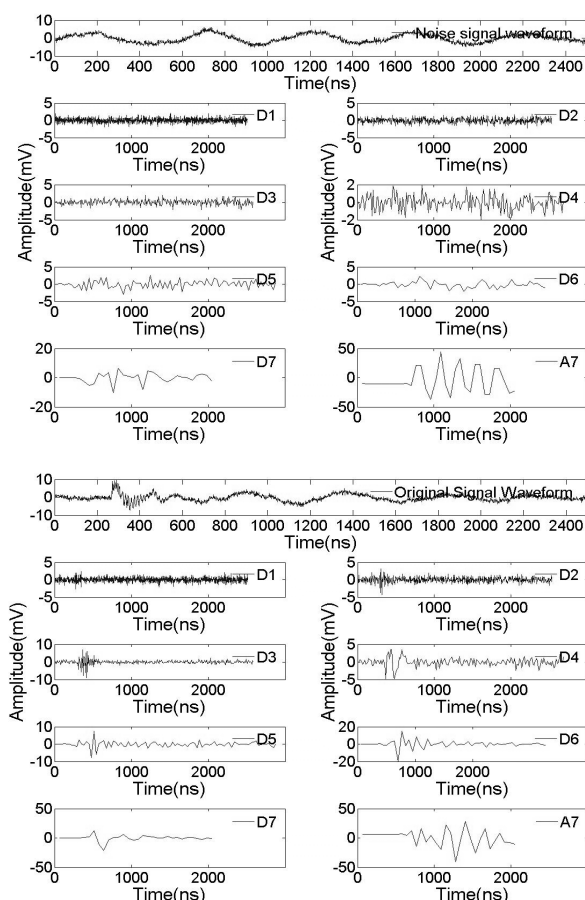


Figure 8: Wavelet decomposition coefficients

As shown in figures above, the detail coefficients at level 3 (WDEC3) represents a better discrimination between the noise and useful PD signal. Taking the level 3 detail wavelet decomposition coefficients as the feature for SVM discrimination, with 100% training accuracy, the identification rates are shown in Table 1.

Conclusions

The feasibility of using hardware and software to eliminate or discriminate electro-optic modulator

system noise has been assessed. Both methods can achieve promising results and are easy to implement. The wavelet decomposition coefficients based SVM represents a better performance. The measurement sensitivity of the whole system mainly relies on the sensitivity and output power of the PD detection sensor.

Table 1: Identification rates by using WDEC3 feature.

Data sets	WDEC3
Noise2	100% (2800/2800)
30pC	99.4643% (2785/2800)
40pC	99.8214% (2795/2800)
50pC	100% (2800/2800)
70pC	100% (2800/2800)
90pC	100% (2800/2800)
110pC	100% (2800/2800)
130pC	100% (2800/2800)

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