

Partial Discharge Classification Using Acoustic Signals and Artificial Neural Networks

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Abstract— the goal of the research presented in this paper is to classify controlled partial discharges generated under different test conditions using acoustic measurement technique and pattern recognition tools based on artificial neural networks (ANN). The sound/acoustic signals produced by discharges are recorded using an acoustic sensor. An envelope detection technique is then applied in order to transform the acquired acoustic signals into a low-frequency signal. The dominant frequency components of the envelope were used as input feature vectors for the developed ANN-based classifier. The results demonstrate an average success rate of 91 % with respect to the classification of the previously measured acoustic signals.

I. INTRODUCTION

The demand for partial discharge (PD) monitoring techniques has increased substantially considering the adverse effects of partial discharge on electrical insulation systems. In existing non-conventional measurement techniques available for the predictive maintenance of high voltage equipment, acoustic sensors are widely used for measuring PD in substations [1-4]. The potential for detecting defects in HV line insulators using these acoustic sensors based on PD pattern analysis has been investigated in this work.

Acoustic techniques are based on the electrical discharges that initiate pressure waves that can be sensed as sound signals. The intensity of the acoustic signal emitted is directly proportional to the energy released by the discharge and the amplitude of the signal is mathematically considered to be the square root of the energy. The sound waves emitted have frequencies ranging from 20 kHz to 100 kHz, which fall outside the audible spectrum [5], [6]. Therefore, the measurement of ultrasonic waves offers the advantage of eliminating audible background noise. The acoustic sensors used for recording these high-frequency signals use amplitude modulation to down-shift the signals within the audio frequency range. This process is accomplished by mixing the electrical signal with a carrier frequency from a local oscillator. Demodulators are employed for extracting audible frequency com-

ponents from the amplitude-modulated signal, with a crackling sound produced by the connection of the signal to a loudspeaker or to an earphone. The major disadvantage of relying on the human hearing to distinguish the audible sound is due to the difference in the level of perception and sensitivity exhibited by individual people. Motivated by a desire to address this drawback, the work introduced in this paper resulted in the development of a pattern-recognition technique for enhancing the acoustic detection and classification of PD signals. The new technique uses an artificial neural network (ANN) platform because of the ability of this type of network to learn from examples without the intensive effort required for defining explicit rules for recognizing input patterns that differ slightly from the learned ones.

A variety of controlled sources of PD generated under laboratory conditions to represent PD originating from hardware and insulation surfaces were employed for this study. A commercially available airborne acoustic signal sensor (MK-720) was used for recording the acoustic signals generated from these controlled PD sources, and the features extracted from the acoustic signals were then fed into an ANN for training and testing.

II. MATERIALS AND METHODS

A. Experimental Setup

Fig. 1 is a schematic of the test setup used for generating and measuring different types of PD. A 150 kV/20 kVA test transformer with a PD level of < 2 pC was employed for generating the high voltage required for producing PD from different sources. As illustrated in Fig. 2, four common types of PD were considered for the multi-class classification analysis: wet surface discharge from a smooth electrode, surface discharge from a smooth electrode, surface discharge from a sharp electrode and PD from a sharp point. The initial PD inception voltage (PDIV) was measured with the simultaneous use of both a standard PD detector (Hypotronics, DDX 9101) and the MK-720 acoustic sensor. The PDIVs recorded using both methods were in good agreement.

B. Feature Extraction

The output of the acoustic sensor is first run through a high-pass filter (HPF) in order to remove the noise, following which, the outer envelope of the filtered signal is detected prior to the final step: fast Fourier transform (FFT) analysis. This process converts the amplitude data of the measured signal from the time domain to the frequency domain. The MK-720 acoustic sensor is equipped with the tools necessary for performing these operations on the measured acoustic signal. A typical FFT for an acoustic signal generated from a sharp electrode is shown in Fig. 3, and the stages involved in the process are identified in Fig. 4.

The intensity of the ultrasound emitted from a PD source varies periodically with the alternating voltage, which means that the amplitude spikes of the processed acoustic signal dominate at the fundamental frequency of the supply voltage and its integral multiples. Details of the signal strength of the 60 Hz, 120 Hz, and 180 Hz frequency components were used as the input feature vector for training the ANN. For the purposes of the analysis, 70 % of the total data collected were used for training, 15 % for validation, and 15 % for ANN testing. The ANN structure used is illustrated in Fig. 5.

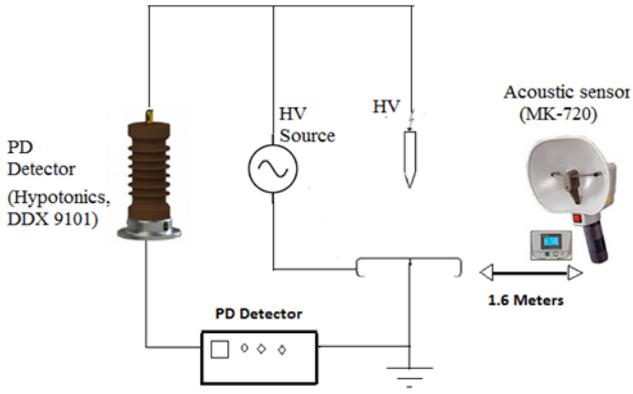


Fig.1. Simultaneous measurement of PD using a coupling capacitor and an acoustic sensor.

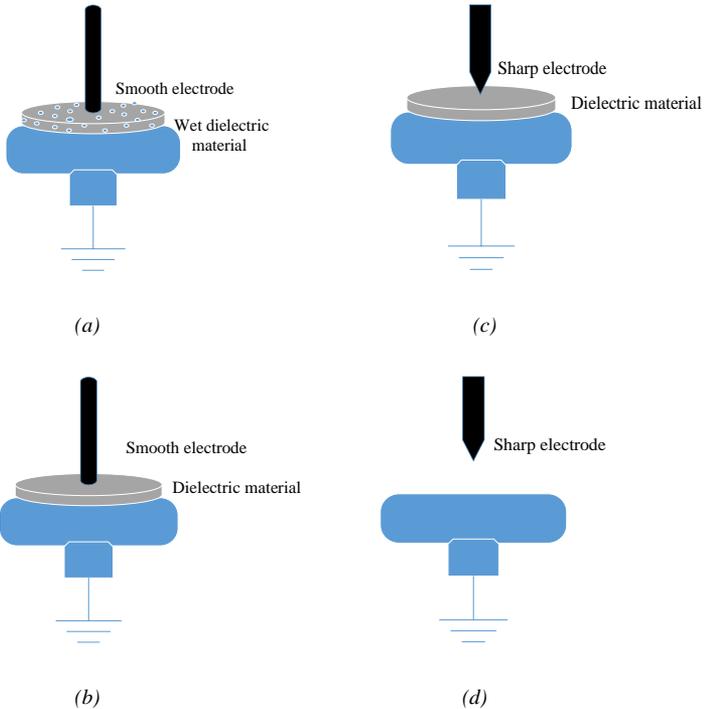


Fig. 2. Illustrations of the geometries used as PD sources: (a) wet surface discharge from a smooth electrode , (b) surface discharge from a smooth electrode,(c) surface discharge from a sharp electrode, and (d) PD from a sharp electrode.

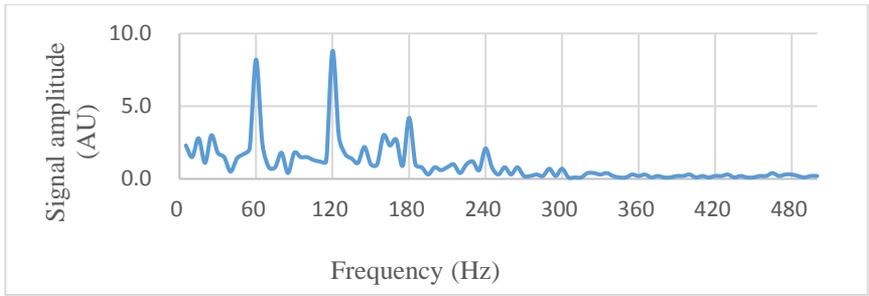


Fig.3. A typical FFT of PD acoustic signal acquired from a sharp electrode.

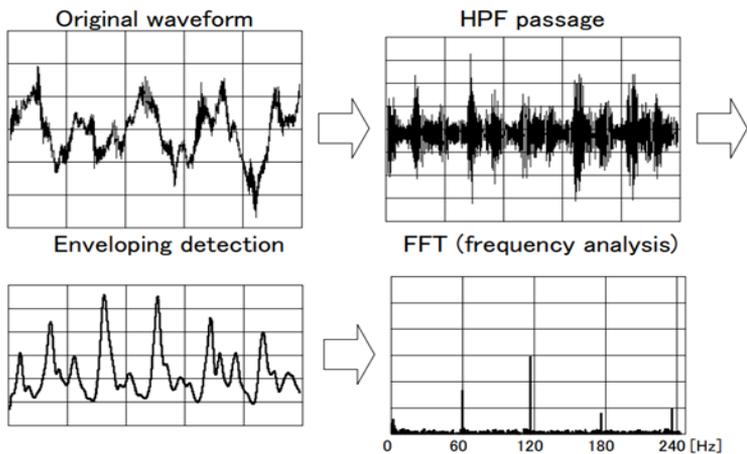


Fig. 4. Envelope detection and FFT operations for converting the measured acoustic signals from the time domain into the frequency domain [7].

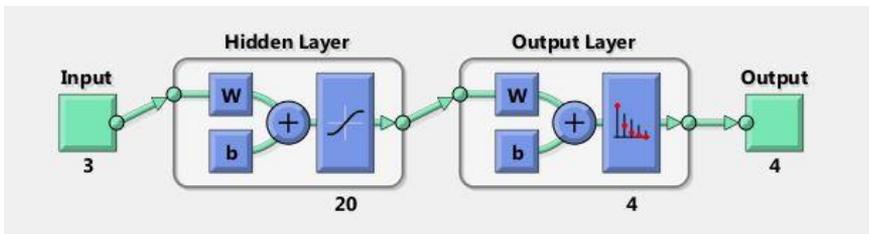
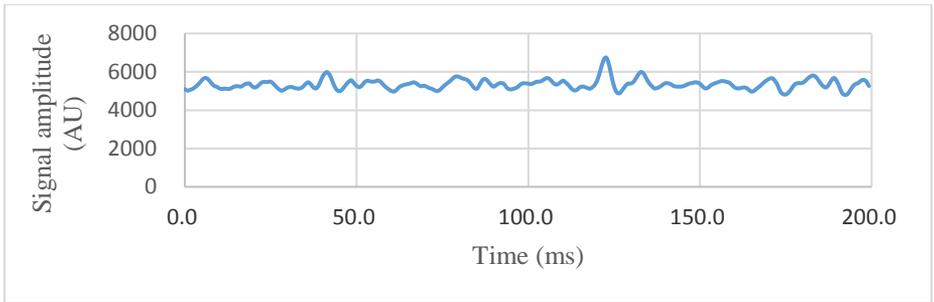


Fig. 5. Structure of the ANN implemented in the analysis conducted for distinguishing PD types: Input feature vectors 3, hidden layers 20, and output classes 4.

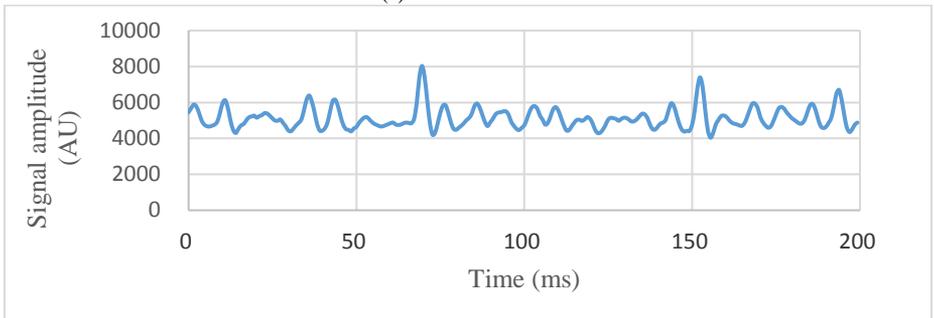
III. RESULTS AND DISCUSSIONS

A. Characteristics of the Measured Partial Discharge Data

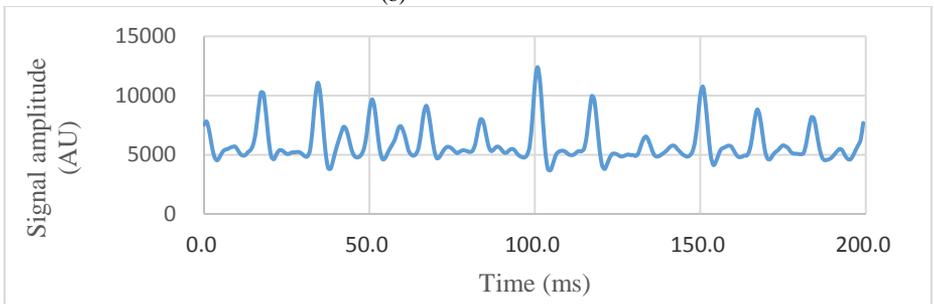
Fig. 6 shows the envelopes measured for the acoustic signals recorded from different PD sources using the acoustic sensor.



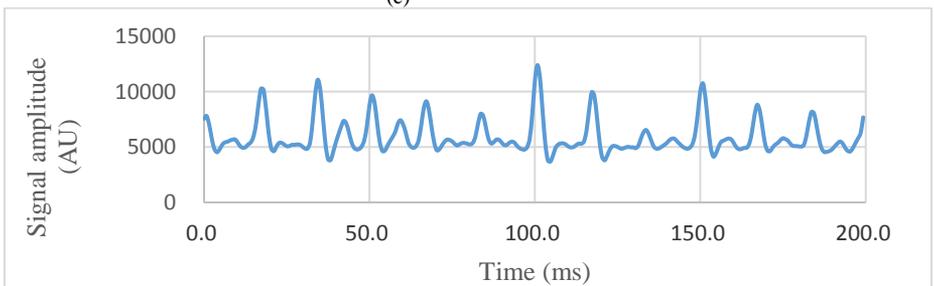
(a)



(b)



(c)



(d)

Fig. 6. Signal envelopes of the acoustic signals measured for (a) wet surface discharge from a smooth electrode, (b) surface discharge from a smooth electrode, (c) surface discharge from a sharp electrode, and (d) PD from a sharp electrode.

It can be seen that each type of discharge has a unique signature. These observable discrepancies in the measured acoustic signals are attributable to differences in the nature of the streamers formed due to the ionization of the air surrounding the electrode. For example, more consistent discharges can be observed for sharp electrodes than for smooth ones. When smooth electrodes are used rather than sharp ones, the amplitude of the spikes and their rate of occurrence are reduced. The tip of a sharp electrode facilitates a more continuous discharge than a smooth surface does. The number of spikes is also the lowest for a wet surface because the discharge causes the water droplets to evaporate, thus eliminating the primary source of field enhancement

B. ANN Analysis

As previously explained, each type of discharge has been shown to have unique characteristics. It has been found that, after FFT is applied to the acoustic PD signal envelope, distinct differences can be observed among the PD generated from the signal magnitudes at 60 Hz, 120 Hz, and 180 Hz components. A 3-D plot based on this information is shown in Fig. 7, which reveals that the four different PD sources have formed distinguishable patterns.

The use of artificial intelligence (AI) can facilitate self-directed recognition of PD types, which could be very helpful, especially for field inspection. With respect to the recognition of different PD sources, the ANN study produced a minimum accuracy level of 90 %, an average level of 91 %, and a maximum level of 91.4 %. A sample confusion matrix that summarizes classifier performance is provided in Fig. 8. The results clearly indicate that high rates of recognition have been obtained. These high classification rates prove that the approach proposed in this paper can successfully differentiate among four PD sources that occur as a result of hardware and insulation surface conditions.

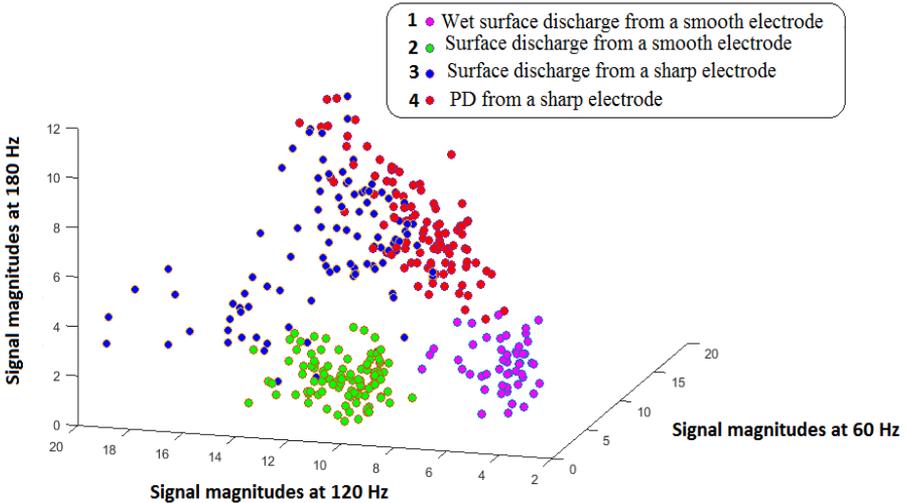


Fig.7. Patterns observed based on 3-D plots of the signal magnitudes at 60 Hz, 120 Hz, and 180 Hz frequency components.

Output Class	1	41 16.8%	0 0.0%	0 0.0%	1 0.4%	97.6% 2.4%
	2	1 0.4%	69 28.3%	0 0.0%	0 0.0%	98.6% 1.4%
	3	0 0.0%	0 0.0%	53 21.7%	8 3.3%	86.9% 13.1%
	4	0 0.0%	0 0.0%	11 4.5%	60 24.6%	84.5% 15.5%
		97.6% 2.4%	100% 0.0%	82.8% 17.2%	87.0% 13.0%	91.4% 8.6%
	1	2	3	4		
	Target Class					

Fig 8. Typical confusion matrix showing individual class recognition rates and total classifier efficiency with respect to distinguishing different PD classes: Class-1 = wet surface discharge from a smooth electrode; Class-2 = surface discharge from a smooth electrode; Class-3 = surface discharge from a sharp electrode; Class-4 = PD from a sharp electrode.

IV. CONCLUSION

Based on the laboratory experiments conducted, the following conclusions can be drawn:

- 1) Distinguishable patterns observed using acoustic signal magnitudes at 60 Hz, 120 Hz and 180 Hz further facilitated employing the ANN for differentiating PD sources with signal magnitude data at 60 Hz, 120 Hz and 180 Hz as input features.
- 2) The developed classifier exhibited an average recognition rate of 91 % with respect to classifying the four different types of partial discharges considered in this study.

The ANN classifier presented in this work using acoustic PD data has potential to analyze partial discharges generated in practical insulation systems.

V. ACKNOWLEDGEMENT

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