Classification of common discharges in outdoor insulation using acoustic signals and artificial neural network

Satish Polisetty¹, Ayman El-Hag¹ ⇓, Shesha Jayram¹
¹Electrical and Computer Engineering Department, University of Waterloo, Waterloo, Canada
⇓ E-mail: ahalhaj@uwaterloo.ca

Abstract: Condition monitoring of outdoor insulation systems is crucial to the integrity of distribution and transmission overhead lines and substations. The objective of this study is to use a commercial acoustic sensor along with artificial neural network (ANN), to classify different typical types of discharges in outdoor insulation systems. Next, ANN was used to distinguish between five common electrical discharges that were generated under controlled conditions. For both controlled samples and full insulators, a recognition rate of more than 85% was achieved.

1 Introduction

Overhead lines supported by outdoor insulators have been used by utilities at both the transmission and distribution voltage levels. Outdoor insulators play a critical role as they insulate the high voltage power line from the grounded tower. However, due to pollution accumulation, outdoor insulators may suffer from flashover leading to power interruption. These flashovers may lead to sustained faults which will result in power system lock-outs as a means of preventing damage to the overhead assets. This type of disruption can be very costly; as the insulators need to be either cleaned of the contaminant or be replaced because of physical damage leading to the system shut down for hours or days. Therefore, monitoring of outdoor insulators is crucial to the integrity of the power grid.

Both ceramic and non-ceramic insulators have been used as outdoor insulators. Non-ceramic insulators show several merits over ceramic insulators, like lightweight and their excellent pollution performance [1]. Hence, most of the newly installed insulators in North America are non-ceramic insulators. However, ceramic insulators are older than non-ceramic insulators and nearly 150 million porcelain suspension insulators are estimated to be currently deployed in the North American grid [2]. A significant number of these ceramic insulators suffer from different types of defects, approaching their end of life and hence need to be identified to avoid complete line failure.

In ceramic insulators, partial discharge (PD) can be initiated because of electric field enhancement due to surface pollution, internal crack, and/or hardware accessories. Moreover, when a water film builds on the insulator surface, this will lead to leakage current (LC) development. Since the LC density is not homogeneous along the insulator surface, in some areas enough heat develops to evaporate the water layer, forming dry bands; resulting in arcing across these dry areas called dry-band arcing (DBA).

When PD and DBA occur, several physical phenomena occur like acoustic emission (AE), electromagnetic (EM) radiation, light emission, or LC signals. Hence, different transducers can be utilised to monitor PD and DBA. Most of the published research focuses either on the measurement of PD, or DBA; but usually, there is a lack of comprehensive approach, which can be used to detect both types of discharge activities.

For PD monitoring, several techniques have been investigated. High-frequency current transformer has been used to detect PD activities resulted from artificially polluted outdoor insulators [3]. It has been found that the signature of the captured PD signal depends significantly on the pollution severity level. Moreover, PD for both ceramic and non-ceramic insulators was measured using radio frequency (RF) antenna in laboratory conditions [4]. It has been reported that there were clear differences in the PD spectra associated with non-ceramic and ceramic samples [4]. Furthermore, an RF antenna was successfully used to detect PD in ceramic insulators and identify damaged ones without specifying the damage type [5].

RF antenna along with machine learning (ML) were used to detect and identify different defects in ceramic insulators [6]. Recognition rate of more than 95% was reported. The main short coming of the proposed system is the relatively high cost of the RF data acquisition system. A fibre optic-based sensor to detect PD has been employed on 500 kV string insulators [7]. The sensor used has the advantage of immunity to EM radiation, but the overall system is complex to implement.

DBA, however, has been mainly monitored directly using current measurements. LC can be either measured as a voltage drop across a shunt resistor or through magnetic coupling using a current transformer. It has been found that the level of low-frequency harmonics in DBA, is highly correlated to both the degree of insulator surface damage [8] and the likelihood of flashover occurrence [9].

Since PD is a high-frequency phenomenon (MHz – GHz range), and DBA is a low-frequency phenomenon (100’s of Hz), most of the existing techniques cannot be used to simultaneously measure both PD and DBA. Alternatively, ultrasound AE sensors have been used to measure both PD and DBA [10, 11]. Measuring both PD and DBA simultaneously is a cost-effective option for power utility companies. However, the major disadvantage of this approach is the difficulty to identify the source of the measured signal, i.e. PD or DBA. ML has been implemented to identify different types of defects on controlled polymer samples [12, 13]. Moreover, ML along with image processing has been used to identify physical damage in ceramic insulators [14, 15]. However, image-based techniques can only detect visible damages and cannot detect internal defects.

From the aforementioned discussions, it can be stated that there is a lack of a comprehensive and cost-effective condition monitoring technique that can be used to identify different types of defects in ceramic insulators. The objective of this paper is...
employing AE techniques to assess the condition of both controlled samples and line insulators. The research investigates the possibility to distinguish between contamination and physical damages of line insulators by measuring the AE resulted from electrical discharges.

2 Materials and methods

2.1 Experimental setup

Fig. 1 Experimental setup showing the simultaneous measurement of PD using coupling capacitor and acoustic sensor

Fig. 2 Five controlled PD sources generated in the laboratory to evaluate the use of AE in PD detection
(a) Sharp point to ground plane, (b) Surface discharge with healthy dielectric medium, (c) Internal PD with spherical electrode & defective dielectric medium, (d) Surface discharge with smooth electrode & healthy dielectric medium, (e) Wet surface discharge with smooth electrode & healthy dielectric medium

Fig. 3 Porcelain insulators with different defects
(a) Crack, (b) Hardware corona generated using a thin wire wound around the insulator cap

Fig. 4 Study of sensitivity of the measuring device through
(a) Variation in the linear distance and, (b) Variation in the angular distance by keeping the linear distance constant

2.1 Experimental setup

Fig. 1 shows the schematic diagram for the overall setup used to generate and measure different types of PDs. Five common types of PDs are considered for the multi-class classification problem as shown in Fig. 2. The test was extended to study the possibility to detect different defects in practical ceramic insulators. These defects include cracks (Fig. 3a), hardware corona (Fig. 3b), and wet surface discharge due to surface contamination. A 150 kV/20 kVA transformer with PD level less than 2 pC is used to generate the required high voltage to initiate PD in the test samples. Commercially available acoustic sensor (MK-720) with 40 kHz as the centre frequency with a frequency range of 16–80 kHz is used to record the PD AEs. A classical PD detector is employed to measure simultaneously PD along with the acoustic sensor. The
The experimental setup used to investigate the effect of the captured acoustic signal sensitivity as a result of a change in distance and angle of measurement on the classification of PD sources is shown in Fig. 4. The distance \( D \) represents the distance between the acoustic sensor and PD source, \( H \) is the vertical distance from the floor level to the PD source and \( h \) is the vertical distance from floor level to the acoustic sensor.

### 2.2 Application of ANN

The MK-720 acoustic sensor is provided with internal signal conditioning circuits. First, the output of the acoustic sensor run through a high-pass filter to remove the noise, following which, the outer envelope of the filtered signal was detected prior to the final step, which was the application of a fast Fourier transform (FFT). The signal conditioning stages are identified in Fig. 5.

A typical measured acoustic signal and its FFT from a sharp electrode are shown in Fig. 6.

The intensity of the AE originated from a PD source varies periodically with the alternating voltage. The acoustic sensor uses the amplitude modulation technique where a carrier wave with a particular frequency is changed according to the intensity of the audio signal. Here, the sensor has inbuilt technology to use a carrier waveform frequency same as the supply voltage frequency, which means that the amplitude spikes of the processed acoustic signal dominate at the fundamental frequency of the supply voltage and its integral multiples. Hence, the acoustic signal components at 60, 120 and 180 Hz were used as the input feature vector for the ANN.

The structure of the two implemented ANNs is presented in Fig. 7. The first ANN (Fig. 7a) was used to distinguish between five different controlled PD sources. The input feature vector was the 60, 120 and 180 Hz frequency components of the acquired PD signal envelope. A total of 450 test data have been collected from the five different PD sources. The second ANN (Fig. 7b) was implemented to classify three different defects in ceramic insulators.
insulators and used three input feature vector (same as the first ANN). 150 input data sets from the three defects of line insulators were collected. The data for both neural networks were randomly mixed and 70% of the total data collected were used for training, 15% for validation, and 15% for testing of developed ANN classifier. This random mixing of data was repeated for 5 times and the average recognition rate was reported in this study.

3 Results and discussions

3.1 Classification of controlled PD sources

The average classification accuracy obtained from the ANN classifier for the five different controlled discharges is depicted in Table 1.

It is apparent from Table 1 that a relatively high overall classification rate was achieved with an average recognition rate of 92% for five different trials. The relatively high classification rate is due to the nature of the measured PD acoustic signal envelopes. Examples of two envelopes for classes I and V are shown in Fig. 8. Each envelope has a distinct signature. The same was observed for other PD signal envelopes. For example, it has been observed that the amplitude and repetition rate of the envelope spikes are relatively high for the discharge from sharp electrodes compared to those from a smooth electrode. Differences in the acoustic signal envelope signatures are due to the different types of streamers formed on the dielectric surface and/or around the high voltage electrode.

Moreover, the 3D plots for the 60, 120, and 180 Hz for the five different discharges envelopes are shown in Fig. 9. It is evident from Fig. 9 that the five different discharge types are separable with some overlap between the classes which explains the high recognition rate.

3.2 Effect of distance on the classification accuracy

To quantify the detection sensitivity of the acoustic sensor, measurements are made with corona and surface discharge at a distance of 150, 200, 250 and 300 cm between the PD source and the acoustic sensor. Fig. 10 depicts the effect of the distance on the magnitude of the 60 Hz component of the corona signal. It is apparent that a decreasing trend is evident and the same trend was noticed for both the 120 and 180 Hz. It is worth mentioning that increasing the distance did not result in overlap between the frequency components of the same class, but caused overlap between different classes that resulted in reduction in the classification accuracy as described below.

To investigate the influence of distance on the classification accuracy, two classifiers were tested, one trained with only the data at 150 cm (ANN 1) and the other was trained with data from all distances (ANN 2). Table 2 summarises the recognition rates obtained from the two classifiers.

Table 1 Recognition rates for the standalone ANN classifier data for five controlled PD sources

| Class | Recognition Rate |
|-------|------------------|
| I     | 86.86            |
| II    | 97.98            |
| III   | 97.28            |
| IV    | 90.46            |
| V     | 86.54            |
| Total | 92.06            |

<sup>a</sup>Class-I (wet surface discharge from a smooth electrode), <sup>b</sup>Class-II (dry surface discharge from a smooth electrode), <sup>c</sup>Class-III (internal discharge from defective dielectric material), <sup>d</sup>Class-IV (dry surface discharge from a sharp electrode), and <sup>e</sup>Class-V (corona).
Both classifiers showed a decreasing trend in their accuracies, however, ANN 2 showed consistent higher accuracy. Nevertheless, ANN 1 still provides accuracy higher than 80\% when tested at distances up to 250 cm. So, to achieve a robust classifier, it is paramount to train the classifier at different distances.

### 3.3 Effect of measurement angle on the classification accuracy

The attenuation in the signal strength as a result of the change in the angle of measurement is studied by placing the acoustic sensor at different angles (5°, 20° and 30°) as defined in Fig. 4. The results reveal that the change in the angle has minimum effect on the 60 Hz component as depicted in Fig. 11. Similar behaviour was observed for the 120 and 180 Hz components.

Subsequently, the influence on the recognition accuracy as a result of changing the angle between the acoustic sensor and the PD source is investigated. An ANN classifier was trained using data measured at a deviation angle of 0° from the line of sight and then was tested using data recorded at 5°, 20°, and 30° deviation angles. The results are shown in Table 3. Unlike the influence of distance on the classification accuracy, it is evident that changing the angle does not impact the classification accuracy. This can be attributed to the fact that changing the angle does not influence the strength of the received signal by the acoustic sensor as evident in Fig. 11.

### 3.4 Classification of defects of ceramic insulators

PD measurement using acoustic sensor along with ANN have been employed to identify three types of defects in ceramic insulators. The defects were corona (class I), crack (class II) and surface discharge (class III). Table 4 shows the average recognition rate obtained from five sets of testing data conducted on the three classes of single and string insulators, respectively.

Both classifiers showed a decreasing trend in their accuracies, however, ANN 2 showed consistent higher accuracy. Nevertheless, ANN 1 still provides accuracy higher than 80\% when tested at distances up to 250 cm. So, to achieve a robust classifier, it is paramount to train the classifier at different distances.

### Table 2 Comparison of recognition rates from two ANNs: Effect of distance on signal recognition

| Test Data | ANN 1 | ANN 2 |
|-----------|-------|-------|
| training information | trained only with data collected at 150 cm from the source | trained with the total distances from source |
| data collected at 200 cm, \% | 90 | 98 |
| data collected at 250 cm, \% | 82.7 | 92.2 |
| data collected at 300 cm, \% | 70.2 | 87.8 |

### Table 3 Comparison of recognition rates from two ANNs: Effect of acoustic sensor angle change on signal recognition.

| Training Data | Recognition rate, \% |
|---------------|----------------------|
| test with 5° of deviation from the source | 84.6 |
| test with 20° of deviation from the source | 83.8 |
| test with 30° of deviation from the source | 85.8 |

### Table 4 Average recognition rates for acoustic data recorded from a single-disc line insulator and string of three insulators

| Testing case | Class I | Class II | Class III |
|--------------|---------|----------|-----------|
| single-disc insulator | 100 | 86.18 | 83.06 |
| string of three insulators | 100 | 83.36 | 80.02 |

### Table 5 Average recognition rates obtained from an ANN classifier trained with data collected from a three-disc insulator string with a cracked middle disc

| Class | Class I | Class II | Class III |
|-------|---------|----------|-----------|
| 80.66 | 83.64 | 96.58 |

PD measurement using acoustic sensor along with ANN have been employed to identify three types of defects in ceramic insulators. The defects were corona (class I), crack (class II) and surface discharge (class III). Table 4 shows the average recognition rate obtained from five sets of testing data conducted on the three classes of single and string insulators, respectively.

It is evident from Table 4 that perfect recognition of corona discharge has been achieved. On the other hand, a recognition rate of more than 80\% was achieved for the other two classes. This difference in the recognition rate can be explained by showing the 3D plot of the input feature vector for both the single disc and the insulator string, Figs. 12 and 13, respectively. It is evident that the
The acoustic signal components at 60, 120 and 180 Hz were found to be effective in decreasing the recognition rate. On the other hand, no impact on the recognition rate has been found from changing the angular distance.

- The study was extended to include the classification of defects and contamination conditions in both string and individual ceramic insulators. In this regard, the classifier produced a recognition rate of more than 85%.
- Varying the position of a cracked insulator disc within a string has only a very small effect on the classification accuracy.

To further enhance the classification accuracy of the proposed system, larger database is collected, and the authors are intending to utilise deep learning.

5 References

[1] Gorur, R.S., Cherney, E.A., Burnham, J.T.: ‘Outdoor insulators’ (Ravi S. Gorur, Inc., Phoenix, Arizona, USA, 1999), pp. 179–204
[2] Gorur, R.S., Shaffner, D., Clark, W., et al.: ‘Utilities share their insulator field experience’, Trans. Distrib. World, 2005, 57, (4), pp. 17–27
[3] Chandrasekar, S., Kalaivanan, C., Montanari, G.C., et al.: ‘Partial discharge detection as a tool to infer pollution severity of polymeric insulators’, IEEE Trans. Dielectr. Electr. Insul., 2010, 17, (1), pp. 181–188
[4] Stewart, B.G., Hepburn, D.M., Kemp, L.J., et al.: ‘Detection and characterisation of partial discharge activity on outdoor high voltage insulating structures by RF antenna measurement techniques’. High Voltage Engineering Symp., Conf. Publication No. 467, London, UK, 1999
[5] Moore, P.J., Portugues, I.E., Glover, I.A.: ‘Remote diagnosis of overhead line insulation defects’, IEEE Power Engineering Society General Meeting, Denver, Colorado, USA, 2004, vol. 2, pp. 1831–1835
[6] Anjum, S., Jayaram, S., El-Hag, A., et al.: ‘Remote diagnosis of overhead line insulation defects’. IEEE Power Engineering Society General Meeting, Denver, Colorado, USA, 2004, vol. 2, pp. 1831–1835
[7] Oliveira, S.C., Fontana, E.: ‘Optical detection of partial discharges on insulator strings of high-voltage transmission lines’, IEEE Trans. Instrum. Meas., 2009, 58, (7), pp. 2328–2334
[8] El-Hag, A.H., Jayaram, S.H., Cherney, E.A.: ‘Fundamental and low frequency harmonic components of leakage current as a diagnostic tool to study aging of RTV and HTV silicone rubber in salt-fog’, IEEE Trans. Dielectr. Electr. Insul., 2003, 10, (1), pp. 126–136
[9] Suda, T.: ‘Frequency characteristics of leakage current waveforms of a string of suspension insulators’, IEEE Trans. Power Deliv., 2005, 20, (1), pp. 481–487
[10] Al-geelani, N.A., Piah, M.A.M., Saeh, I., et al.: ‘Identification of acoustic signals of internal electric discharges on glass insulator under variable applied voltage’, Int. J. Electr. Comput. Eng., 2016, 6, (2), pp. 827–834
[11] de Barros Bezerra, J.M., Lima, A.M.N., Deep, G.S., et al.: ‘An evaluation of alternative techniques for monitoring insulator pollution’, IEEE Trans. Power Deliv., 2009, 24, (4), pp. 1773–1780
[12] Polisetty, S.K., Jayaram, S., El-Hag, A.: ‘Enhancing partial discharge classification using acoustic signals and artificial neural networks’. ESA/ IESJ / IEEE-IAS Joint Meeting, Boston, USA, 18-20 June 2018
[13] El-Hag, A., Mukhopadhyay, S., Al-Ali, K., et al.: ‘An intelligent system for acoustic inspection of outdoor insulators’. 3rd Int. Conf. on Condition Assessment Techniques in Electrical Systems (CATCON), IIT Ropar, India, 16–18 November 2017, pp. 128–131
[14] Kang, G., Guo, S., Yu, L., et al.: ‘Deep architecture for high-speed railway insulator surface defect detection: demonising autoencoder with multitask learning’, IEEE Trans. Instrum. Meas., 2019, 68, (8), pp. 2679–2690
[15] Zhong, J., Liu, Z., Han, Z., et al.: ‘A CNN-based defect inspection method for catenary split pins in high-speed railway’. IEEE Trans. Instrum. Meas., 2019, 68, (8), pp. 2849–2860
[16] Instruction manual for Corona discharge checker MK-720.