The sounds of partial discharge

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Abstract
Partial discharge (PD) is a critical phenomenon that often occurs in medium and high voltage electrical equipment due to insulation faults and generates various types of acoustic emissions. The characteristics of the PD signal depend on the type of equipment, physical condition, operating voltage, and insulating substances used (e.g., gases, oils, nonmetallic solids). Corona, arcing, and surface discharges are the most common PD faults. Usually, these faults are quantified by electrical and acoustic detection methods. PD signals have different levels of acoustic emission, represented by different time-frequency characteristics. Currently, the analysis of PD data, detection and classification of faults is done manually or semi-automatically by experts. This paper provides the current state of the literature on acoustic condition monitoring of partial electrical discharges in various electrical equipment (e.g., transformers, cables, switchgears). The typical approaches used in the acoustic measurement and feature representation of signals for PD defect recognition are presented in detail. Expanding the possibilities for automated detection of PDs using signal processing and neural networks is also discussed for future research.

Keywords: Partial discharge, acoustic emission, detection and machine learning

Introduction
Power supply to electrical equipment can be generally carried out on the basis of three main functional stages in a power supply system, namely power generation, transmission and distribution. These stages function with the variety of high voltage electrical equipment such as rotating machinery, power and current transformers, high voltage transmission cables, switchgears, etc. [1], [2], [3]. To ensure an uninterrupted power supply, they must be kept in a faultless condition. The maintenance of such complex networks is a great challenge that requires regular condition monitoring. Electrical insulation failure is one of the biggest problems that can occur in power systems for a variety of reasons, including insulation aging, electrical component failures, unexpected loads, and overvoltages.

Early detection of PD can prevent system failures, as PD is a recurring event may become more severe over time. Acoustic emission (AE) of electric discharges is an indication of insulation failure. Depending on the electric equipment and physical state of insulation materials (gases, liquids and solids), the characteristics of the sound will change. The frequency spectrum of PD noises are in audible to ultrasonic range [4]. At the moment, quantification and data analysis of various PDs is performed manually or semi-automatically by domain field experts using advanced signal processing techniques and statistical algorithms [5]. In this paper, we discuss the AE characteristics of various PDs commonly encountered in different electrical systems, such as corona, arc, and surface discharges, and various signal processing techniques for feature extraction, such as statistical methods and time-frequency representations. In addition, we address some of the potential problems we encountered during the literature review on machine learning (ML)-based PD detection methods and propose some countermeasures to overcome these challenges.

Related Work
Electrical discharges dissipates energy partially as an indication of insulation damage. The energy emission from the insulation damage location can occur in various forms, e.g. as electromagnetic radiation in the form of radio waves, as AE, as lightning and heat, and as chemical decomposition. The type of PD indication vary depending on the type of electrical equipment, insulating medium, geometry of the equipment and power supply (AC/DC) [6].

According to IEC 60270, PD detection can be performed conventionally using electrical measurement methods. Here, the voltage and current pulses of the desired electrical assets are analyzed at very high frequencies [7]. Based on the insulation damage type the characteristics of the PD signal varies. Discharge signals can be observed as a fast transient current pulses [8]. According to IEC TS 62478, the standard frequency ranges for acoustic and electromagnetic measurements of PD are typically between 3-30 MHz for HF, between 30-300 MHz for VHF and UHF between 300 MHZ and 3 GHz [4].

PD monitoring based on acoustic measurements has several advantages compared to other measurement methods such as electrical, optical and chemical methods. The biggest advantage is that acoustic measurements are immune to electromagnetic radiation and have good electrical resistance. The sensors do not require physical contact with the desired electrical equipment, can be easily installed on site and are inexpensive compared to other methods [9].

The AE based PD diagnosis can be done by PD detection, identification, classification, and localization in various electrical systems to measure and estimate the early failures. Compared to other electrical components, power transformers are the most affected by PDs, and the AE is used as the main source to detect and locate damage [2].

In general, the detection and classification of PDs can

be done in two ways: manually by experts or automatically by statistical or data-driven methods. The first step is the same in both cases: measured PD signals are processed with signal processing algorithms, relevant features are extracted and analyzed by statistical or time-frequency representations. In the second step, PD experts analyze the signals to detect the abnormal behavior and patterns of the signals, which can be considered as a manual approach that takes a lot of time since the signals can be monitored offline [10]. Nowadays, manual approach can be replaced by automated by ML and deep learning (DL) algorithms for accurate and fast failure estimation. Development and deployment of automated algorithms such as ML and DL algorithms can be done by domain field experts [10]. PDs can occur anywhere on the surface or inside the insulating material, which may not be visible from the outside due to shielding layers. Therefore, localization of the PD events is critical for diagnosis. AE information of PDs support the PD event localization. There are several sound localization techniques that use multiple sensors around the desired device that measure signals and calculate the time difference of arrival, the direction of arrival, and the received signal strength [11].

Acoustic emission of PD

The definition of PD according IEC 60270 is that "a localized electrical discharge that only partially bridges the insulation between conductors and may or may not occur adjacent to a conductor" [12]. Generally, electrical discharges occur when the local electric field exceeds the dielectric strength threshold of the insulating material. The AE is the consequence of the collision of molecules at the location of the PD. Discharges that occur on the surface of the insulation are called external discharges such as surface discharges or corona. Discharges that occur inside the insulating material are referred to as internal discharges such as cavity discharges. According to IEC TS 62478 standard, the frequency range of acoustically emitted discharge signals are in the audible to ultrasonic range (10 Hz - 300 kHz) [4]. The sounds of PDs from various electrical devices measured in the high voltage laboratory can be found here [13].

AE characteristics of PD signals

PD signals are inherently very transient and AE signals appear in the time domain as a series of pulses. The width of the PD pulse, the repetition pattern, and the amplitude of these signals vary depending on the discharge type. The intensity of the discharge signals can vary depending on the electric field they transmit. The higher the input voltage of the system, the louder the signal can become. To generate the AE of PD signals, we performed four different systematic experiments in the 250 AC high voltage laboratory. We used four different electrode arrangements to generate different types of acoustic discharge signals. To understand the signal properties, we first analyze the temporal properties of the PD signals. As described earlier, the PD signals appear as a sequence of pulses. To identify the property of a single pulse, we analyzed the 40 ms audio excerpt shown in Figure 1.

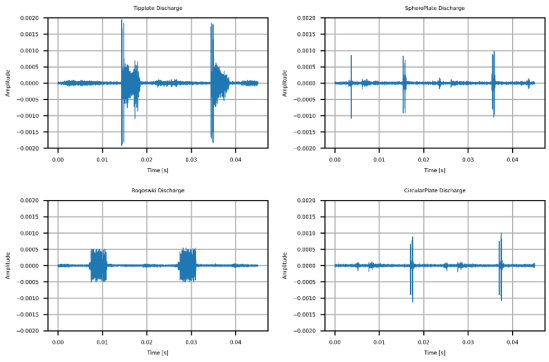

Figure 1: Acoustic signals obtained from the four various PD experiments

As shown in the bottom two images in Figure 1, they appear to be similar due to the similar electrode shape (spherical plate and circular plate). To better interpret these signals, we calculated the power spectral density (PSD), which analyzes frequency versus power. It can be observed that each discharge signal has a unique power variation in different frequency range, as shown in Figure 2.

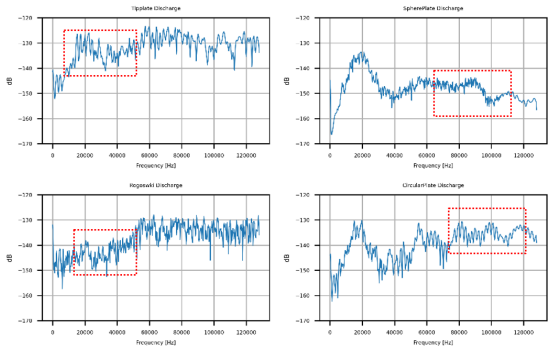

Figure 2: Power spectral density of various PD signals

Signal processing and feature extraction methods

To interpret the PD analysis for discharge identification and classification, various statistical features are calculated from the raw PD data, such as the number of discharge pulses per period, mean, skewness and kurtosis of the pulse height or phase and amplitude distributions, and so on [14]. The statistical features provide a characterization of the PD pattern, which can be useful for identifying the PD type. These statistical features popularly applied on spectral components of the applied voltage data, the ideal AC voltage signal is a pure sinusoidal but during the event of PD, phase and amplitude distortions can be observed [15].

AE from discharges typically characterized by the time-frequency representations such as STFT spectrograms [5], [14]. This method seems to be extract relevant features from the raw signals for neural network (NN) training for automated detection and classification. In addition, interestingly, Mel spectrograms used for human-

perceivable distance signals such as speech and ambient noise also provided better results for ultrasonic distance detection [5], In addition, we have also found in the literature another powerful tool for signal analysis and classification, namely the wavelet transform [16]. Unlike the Fourier transform, the wavelet transform provides the frequency information contained in the signal with a high resolution in the time domain. Moreover, the real discharge signals from various insulation defects are non-stationary in nature. Localization of anomalous short-term events such as discharges in the time domain could be more accurate with the continuous wavelet transform (CWT). To feed neural networks for signal classification, one-dimensional features extracted from the wavelet transform are converted into two-dimensional representations called scalograms [2], [16].

PD detection, classification and localization

PD monitoring based on AE in various electrical systems can be performed manually by professionals in the field and semi-automatically using signal processing algorithms and data analysis tools. Although, to build an AE-based application for PD detection, identification, and localization, different authors have used different feature extraction, ML, and DL techniques over the years. In this section, we briefly review some of the interesting and popular methods for monitoring PDs in various electrical systems. As PDs are common in power transformers, we first considered AE-based PD monitoring papers for power transformers. W. Sikorski et al. proposed a high-resolution multiple-signal method in which frequency analysis is effectively used to detect AE signal frequency components of PDs in power transformers. In addition, joint time-frequency and CWT analysis is used for categorizing various discharges [2]. M. Kunicki proposed two-stage classification methods using various ML algorithms such as binary decision trees, support vector machines (SVM), K-nearest neighbors (kNN), and an ensemble of decision trees with discrete wavelet transform-based energy patterns as input data for multiclass classification of selected defects in power transformers [17]. Further, M. Harbaji et al. proposed CWT with direct cosine transform coefficients and back propagation based NN method for simulated PD classification from different electrical arrangements [16]. G. Li et al. proposed multi-column convolutional neural network (CNN) architecture to recognize the PDs in gas-insulated switchgears (GIS), where UHF signals with selected temporal, frequency and texture filters are used [3]. The survey by S. Lu et al. [7], S. Barrios et al. [10], W. Raymond et al. [9] summarizes the state of the art in the diagnosis of PD using ML methods. The summary tables in survey articles provide the information on PD application domain (cables, transformers, substations, GIS, etc.), the objective (PD detection, classification, localization), the sensor type (acoustic and ultrasonic microphones, UHF, HFCT, RF sensors, etc.), the methodology (ML and DL algorithms), and the results. It can be noted that the most popular feature extraction methods for PD detection are statistical features, fast fourier transformation (FFT), continuous and discrete wavelet transform, and phase-resolved PD data. The most popular ML and DL methods are SVM, kNN, artificial NN, back propagation based NN and different variants of NN used for PD detection, classification and localization.

Challenges and potential solutions for real-world acoustic monitoring of PD

In this section, we briefly discuss some of the significant challenges that arise when using NN-based solutions for real-world acoustic monitoring of electrical discharges and generic audio detection and classification tasks. In most of the available publications the data used for the development of NN-based PD monitoring algorithms are obtained from artificially generated defects. However, real-world PD events have a dynamic characteristics due to various signal influencing factors, as explained in the introduction section, which are not easy to generate artificially. The sensitivity of discharge signals to various influencing factors affect their characteristics and which can be observed by looking at the data distribution over time. If the data distribution of the training dataset and the target dataset do not match, this can lead to a degradation of the algorithm performance. Considering some of the main issues related to domain shifts, such as inconsistencies with the environment and sensors, we presented several normalization and augmentation methods as countermeasures in our recent publication that can be potential solutions for real-life PD prediction [18] and robust PD monitoring. Insufficient training data and imbalance between multiple PD classes is a further problem. This can be solved by using up/down sampling techniques for datasets and also data augmentation techniques [19]. The transfer learning (TL) technique could also be a possible solution to the problem of insufficient training data. The pre-trained NNs transfer their knowledge by providing their weights. TL can be performed by replacing the last layers with new layers of the already trained model and training the last layers with a new dataset. TL can also be done in another way by using the outputs of the intermediate layers as features, called embeddings, to train a classifier for a new dataset [18], [19].

Conclusions and Future work

In this paper, we have discussed electrical PDs and their acoustic properties, and summarized several acoustic data analysis and feature extraction techniques from previous publications. In addition, we briefly discussed state-of-the-art ML and DL models for automatic PD detection and classification. Most previous automated PD monitoring studies provided good results, but the algorithms were developed using artificial or simulated data. The development of real life PD monitoring algorithms can pose several challenges, such as data acquisition, data scarcity and imbalance, labeling, and domain shift. To realize robust PD monitoring algorithms for in real-world environments, various techniques need to be applied to the data, such as data balancing schemes, data representation, augmentation, and normalization meth-

ods. Moreover, training strategies such as transfer learning and semi-supervised learning could not only improve the performance of PD monitoring algorithms, but also reduce the tedious work of data labeling and data scarcity issues.

In the future, we will investigate the factors affecting the AE of real PDs and analyze their data distribution to develop robust DL-based algorithms for PD monitoring.

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