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ORIGINAL PAPER

# Acoustic emission analysis for corona discharge detection in medium-voltage cubicles: a review

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**Abstract**
This study reviews more than one hundred significant studies on various methods and advances in the detection of partial discharges (PD), with a specific focus on corona discharges (CD) in medium-voltage switchboards (MV) using the acoustic emission (AE) method. Furthermore, the challenges and prospects of this method are discussed. The article delves into several aspects of CD diagnostic research, including detection mechanisms, development of detection tools, source determination, and severity evaluation. Furthermore, this article investigates the impact of different variables such as humidity, applied voltage, and gas pressure on corona discharges and how these factors influence diagnosis. While CD detection in MV cabinets has been extensively reported and investigated, most studies have concentrated on various CD detection approaches in gas-insulated switchgear (GIS), with limited exploration in other areas. In contrast, this report comprehensively addresses numerous features of CD diagnosis in MV cabinets and establishes a framework for further progress. Considering current research trends, a thorough evaluation is anticipated. This review describes the current state of CD detection in the study and development of cubicles. Therefore, it can serve as a reference for researchers conducting further investigations into the real-world impact of this issue on industry.

**Keywords** Corona discharge detection · Medium-voltage cubicle · CD classification · Acoustic emission method

## 1 Introduction

In electrical equipment such as MV switchboards, GIS, and equipment related to high voltage, partial discharges (PD) and corona discharge (CD) may occur, which are discharge phenomena in the insulating material.

These discharges affect only a tiny portion of the dielectric or gas of the insulation [1]. PD can occur due to defects in the insulation of electrical equipment, failures in electrical cabinets are primarily caused by this defect [2]. Insulation will slowly deteriorate due to PD, affecting the electrical equipment's regular operation. Therefore, both the internal insulation condition of the electrical system and the detection of insulation problems are possible with accurate and reliable PD [3]. PD and CD are both electrical phenomena that involve the release of electrical energy in insulating materials. While they share similarities, they are distinct phenomena with different characteristics.

Pulses of current, electromagnetic, acoustic emission, light emission, and other phenomena associated with PD can be employed for its identification [4]. The technique of pulse current (PCM) [5, 6], ultra-high-frequency (UHF) method [7–9], ultrasonic acoustic wave (UAW) method [10], optical detection [11], and transient earth voltage (TEV) method [12] constitute the primary methods for detecting PD and CD in use today.

The primary cause of the development of corona discharge conditions (CD) is illustrated in Fig. 1. Based on numerous observed instances of corona, three main factors contribute to its development: factors of geometrics, spatial, and material contamination [13].

First, geometric factors include sharp edges on conductors, multiple connections, and vulnerable components in switchgear cabinets.

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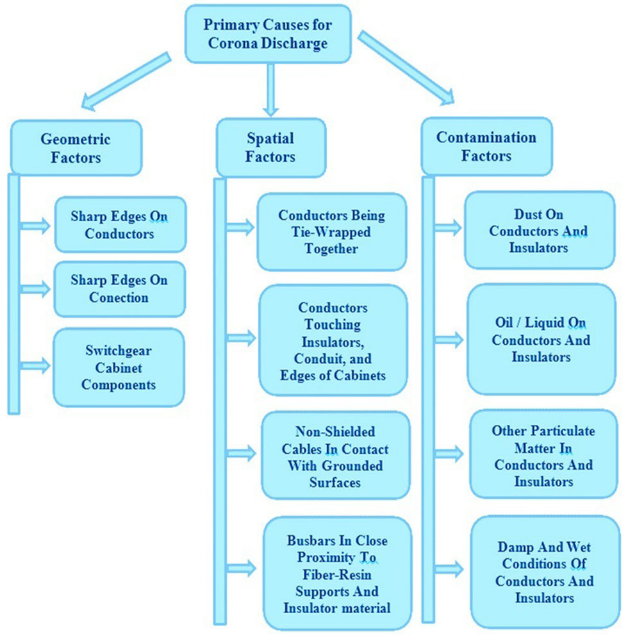


**Fig. 1** The main cause of the development of the corona discharge condition

**Fig. 2** Corona tracks close to bus bars

Secondly, spatial factors involve small air spaces between conductors, insulation boards, and switchgear cabinet components. This may arise from various conditions such as the conductor is bonded, the conductor contacts the insulator, the cable contacts the grounded surface, and the bus bar near the fiber-resin support, as shown in Fig. 2.

Finally, dust and other particulate contamination on conductors and insulators contributes to the occurrence of corona, as depicted in Fig. 3.

While the detectors installed inside the apparatus may exhibit relatively high sensitivity, they can potentially lead to

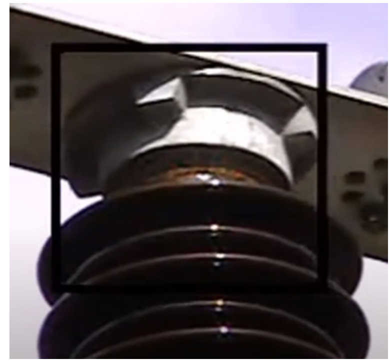

**Fig. 3** Corona discharge formed because of contamination on ceramic bushing

new insulating issues. When assessing the insulation of high-voltage equipment, each method may have its benefits and drawbacks. However, certain detection techniques may prove more effective for specific high-voltage equipment than others.

The sensors proposed in this article are crafted using the acoustic wave approach, a more sustainable process that avoids additional insulation issues while maintaining excellent sensitivity, in contrast to the strategies mentioned above [2, 14–16]. Acoustic detection is commonly employed for GIS flaw diagnostics in factory tests and everyday usage. Several uses of using acoustic methods, but not limited to [17–21]: (a) are nondestructive and noninvasive; (b) strong against electromagnetic interference; (c) free from influence from external capacitors, ensuring that the sensitivity of the measurement is not affected by the capacitance of the object being tested; etc.

Numerous monitoring methods for PD or CD have been recently discovered and proposed. It is essential to provide examples of the shortcomings of these methods and elucidate their functionality. Several review articles in the literature delve into these methods, presenting trends and the state of the art in specific areas [22–24].

This work aims to analyze recent advancements and trends in CD detection, particularly in medium-voltage cubicles, and provide a diagnostic overview. This review focuses on the causes of cubicle damage, elucidates methods of CD detection, clarifies various techniques for identifying isolation defects, and establishes a theoretical foundation for current severity evaluation approaches, concentrating on publications from the last ten years. In addition to highlighting relevant gaps, this review presents a taxonomy for some of the tactics used in the literature, serving as a starting point for additional study on the subject.

## 2 Detection discharge in medium-voltage cubicles

A local electric voltage is produced by PD, an electrical disturbance in the insulator that does not bridge the electrodes. This process decreases high-voltage equipment's insulation life and slows insulation degradation [25]. PD occurs when an electric field exceeds the threshold value and partially breaks down the surrounding medium [26]. If PD behaves transiently, a pulsed current with a nanosecond to microsecond duration is present. Complete damage typically results in insulators losing all information about the PD type [27]. Therefore, constant monitoring is necessary to address the issue at stages [28, 29]. The isolation conditions can be determined using the PD pattern of each type of defect, each having unique degradation characteristics [30].

Corona activity can be monitored through various methods. The most effective approach is to observe the light produced by the corona or to listen to its sound. Corona activity is visible to the naked eye only in very dark conditions. Another method for monitoring corona is by listening to the sound it generates [31]. The noise caused by corona can be described as a hissing sound, often audible to the human ear.

In an air gap with a nonuniform field, electrical failure begins with the emergence of the initial voltage (inception voltage), marking the initiation of the corona occurrence mechanism. Corona discharge occurs when two electrodes (conductors) are positioned with sufficient gaps and under satisfactory environmental conditions with nonuniform terrain, and a sufficiently high voltage is applied. A distinctive characteristic of corona emergence is that the electrode appears luminous, emitting noise and the smell of ozone ($O_3$). With continuous voltage increase, complete electrical failure occurs in a flash jump, where the air between the electrodes becomes conductive, allowing the flow of electric current [32].

Electric tree planting can occur in areas with significant electric fields in the dielectric material due to flaws such as gas cavities, sharp electrode edges, or metal particles. Ultraviolet light and ozone gas are by-products of voids beneath high electrical voltage, leading to the decomposition of the insulator and the creation of emptiness. Repeated cavity generation results in weak points and the formation of an electric tree, ultimately causing destruction. Additionally, due to pollution generating flashover on the surface and high electric field voltage, an electric tree can form on the dielectric surface. An insulator (ceramics, silica, etc.) is present between the electrode pairs, usually causing the removal of the dielectric barrier [33].

Electrical equipment can experience PD, which is the occurrence of discharge in an insulating medium under high voltage (HV). This discharge does not result in a complete breakdown of the gas or dielectric insulation; instead, it occurs locally. Insulation flaws in electrical equipment can lead to PD, a primary factor in GIS failure. PD causes a gradual reduction in insulation, which interferes with the regular operation of electrical equipment. Therefore, the internal isolation status of power equipment may be evaluated, and insulation problems can be detected using accurate and trustworthy PD detection methods [34].

Techniques for measuring PD are based on insulation systems' various physical and chemical processes. To better understand the phenomenon of void discharge, research was conducted for ten years beginning in the 1960s, when this monitoring method was initiated [35]. Another significant advancement was the satisfactory progress made in the late 1970s toward various PD processes such as treeing, flashover, sparks, avalanche, and streamer [36–38]. PD causes the following physical events in a power transformer isolation system: (a) Mechanical vibrations appear, resulting in ultrasonic acoustic waves. (b) The emission of electromagnetic waves at extremely high frequencies. (c) The release of nitrogen and ozone is due to chemical events. (d) The generation of heat and light radiation [39].

To develop automatic PD detection, the PD monitoring system has recently been expanded to include data analysis techniques and sensor technologies [40]. A typical PD surveillance system consists of a PD unit for signal collection feature extraction and a unit for data analysis. Sensors in the PD signal-gathering unit can identify physical activities that release various types of energy. There are two distinct pattern graphs in the PD signal: PD with a time-resolved partial discharge (TRPD) and PD with phase-resolved partial discharge (PRPD) [41]. It can be observed that "q" is a parameter in the PRPD, and "t" is a time parameter in the wave graph, while the q–t waveform is represented in the TRPD. This characteristic is also utilized in PD data processing, which typically employs more innovative pattern recognition methods and uses fuzzy intelligent systems to distinguish between PD and noise or to identify the source of PD [42].

## 3 Partial discharge and corona discharge detection methods

PD can result in a variety of physical events that can be observed: The phenomena may manifest as the presence of gases or changes in the chemical composition [43–47], optical light [48–52], current pulse [53–57], electromagnetic wave [58–62], and acoustic emissions [63–67] which is illustrated in Fig. 4. Electrical and nonelectrical approaches are two primary groups of physical phenomena that allow for the detection and quantification of PD. There are several methods and sensors, as well as disadvantages and advantages, in PD detection presented in Table 1.

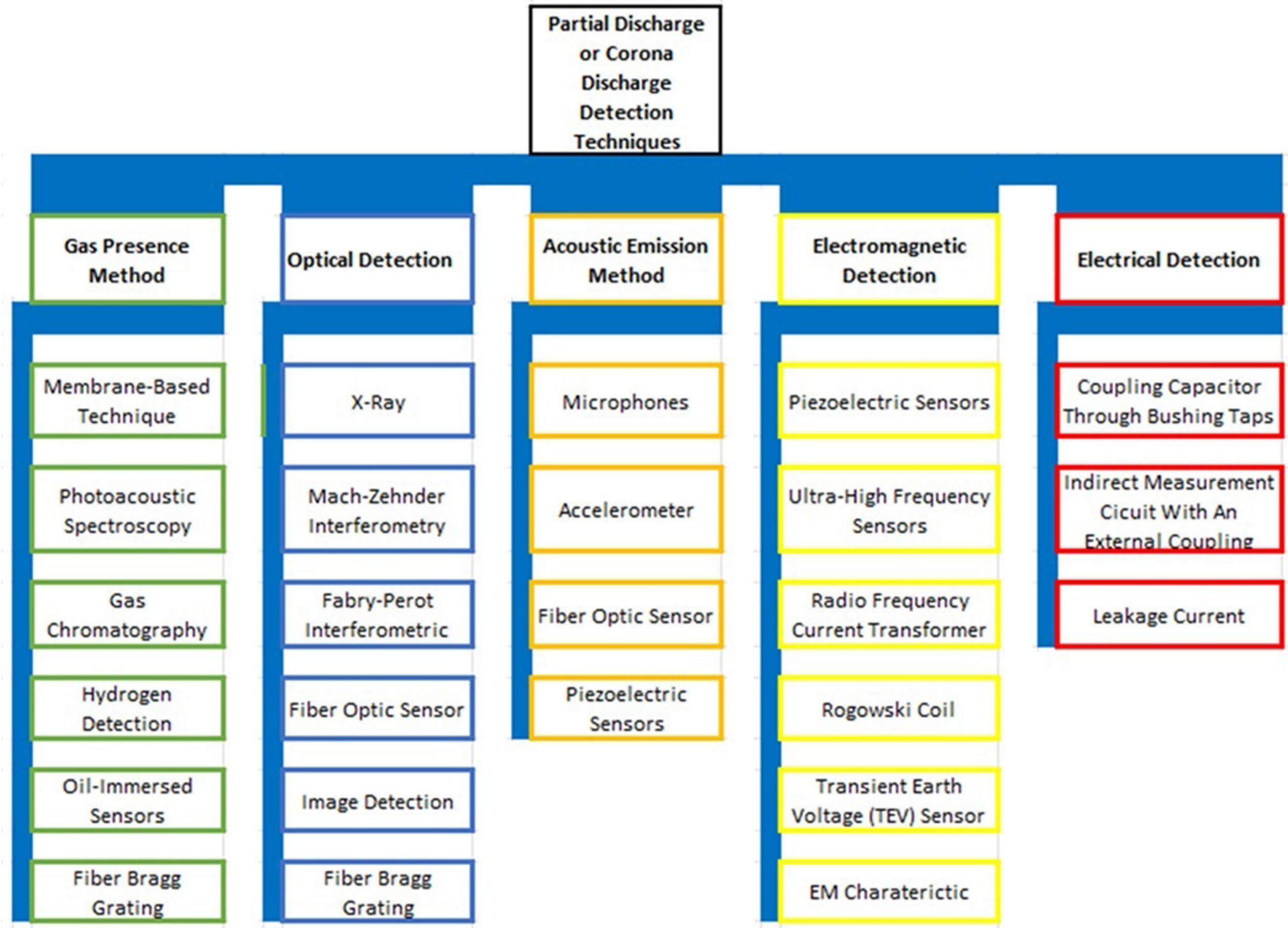


**Fig. 4** Partial discharge and corona discharge detection methods

### 3.1 Chemical and gas presence method

PD occurs in $SF_6$ gas, some of the $SF_6$ molecules decompose, reacting with impurities in $SF_6$, namely $H_2O$ and $O_2$. Various chemical products are formed, including $SOF_4$, $SOF_2$, $SO_2F_4$, $SF_4$, $SO_2$, $CF_4$, $CO_2$, HF, etc. In a GIS, decomposition products are indicators for PD detection. Chemical method detection is almost unaffected by noise and electromagnetic interference [43–47]. In Fig. 5. The electrodes are high voltage, and the breakdown of SF6 is carried out due to corona discharge [68].

Two main chemical testing procedures are used: dissolved gas analysis (DGA) and high-performance liquid chromatography (HPLC). The DGA test identifies the level of dissolved gas released from the transformer during PD (such as hydrogen and methane). However, there is no standard value for the DGA test results and the concentration of dissolved gas in the oil, which correlates with damage to the transformer [23]. Figure 6 illustrates the chemical PD detection technique.

### 3.2 Optical method

PD activity detection in power transformer oil can utilize supporting tools with an optical approach. Mach–Zehnder interferometry (MZI), Fabry–Perot interferometer (EFPI), and Bragg fiber gratings (FBG) are examples of typical PD optical detection sensors [22]. Figure 7 illustrates the essential operation of FBG.

In 2013, an unconventional method of measuring PD in power transformers using fluorescence sensors was proven reliable, shown in Fig. 8. However, studies on the ability of fluorescent sensors to detect PD in transformer oil produced dubious results with several flaws. The correlation between the activity of photons, PD via optical signals, and PD charge restrictions in oil is still being investigated in experiments. Measurements for power transformer oil became achievable in 2014 [22]. However, this is particularly challenging for ancient transformer oils.

In addition to the optical approaches mentioned above, partial discharge (PD) detection can also be done using visual

**Table 1** Methods and sensors system for PD detection

| Method | Advantages and opportunities | Disadvantages and weakness | Sensors application |
|---|---|---|---|
| Chemical or gas presence [22, 23] | Accurately measures and records PD signals for use in the laboratory<br>Very sensitive<br>Online surveillance is possible | Dissolved gas concentrations and various mistake kinds do not correlate<br>The degree of dielectric breakdown is independent of glucose concentration<br>PD source unknown<br>Unclear standards for dissolved gas and glucose in the oil or the level in the transformer | Chemical samples |
| Optical [22, 23] | Utilization is possible for a wide range of chemical and physical parameters<br>Small and light in weight<br>High sensitivity<br>EMI resistance<br>Extensive frequency range<br>Being able to endure high temperatures<br>It is possible to monitor online | The detection of insulation is not practical<br>Non-calibratable<br>Localizing the PD source during surgery necessitates either manual or eye contact | Mach–Zehnder fiber interferometers<br>Multimode fiber<br>Fabry–Perot interferometers<br>Fiber Bragg grating (FBG) |
| Electrical [22, 23] | Statistically significant laboratory recordings of PD signals<br>PD signal with low noise level<br>High sensitivity<br>Minimal signal attenuation<br>Measurements are precise<br>Wide detection field of view<br>It is possible to localize the source of PD | False alarm due to greater sensitivity<br>Vulnerable to noise<br>On-site Measured possible<br>Affected by EMI<br>Long-term monitoring is not possible<br>There is a lot of noise outside<br>Online surveillance is useless | Coupling capacitance |
| Electromagnetic (UHF) [22, 23] | Enhanced immunity to outside noise<br>Extremely sensitive and non-interfering<br>Trustworthy and unaffected by any induced current<br>Appropriate for in-service monitoring or online detection<br>UHF signal activates an acoustic sensor<br>Experiments can be carried out online<br>The PD source can be located | Costly<br>Unable to provide PD load count<br>Highly susceptible to electrical noise produced by radios, televisions, and other electronics<br>There is no calibration technique available (calibration issue) | Sensor for a drain valve<br>Conical monopole antenna, internal sensor<br>Window sensor<br>HFCT sensor |
| Acoustic [22, 23] | Convincing real-time results that can be applied on-site<br>Immune to device noise and electromagnetic noise for online PD detection<br>Multiple sensors can be used to localize the PD source<br>Sensors can be installed without modification<br>Monitoring can be done both online and offline | Low sensitivity<br>Signal interference caused by background noise<br>Data processing complexity | Microphone<br>Piezoelectric<br>Accelerometer<br>Optical fiber |

imaging techniques with cameras. This method utilizes cameras that are sensitive to certain frequencies of light emissions produced by PD activity. The use of digital cameras has proven effective in detecting PD in various electrical equipments [71]. This technique offers the advantage of being able to monitor PD in real-time and noninvasively. However, environmental conditions, such as lighting, temperature, and type of oil material, can affect the accuracy of detection. The implementation of imaging technology in detecting PD is still developing to provide a more accurate and reliable solution in monitoring the performance of high-voltage electrical equipment.

### 3.3 Electrical method

In the electrical detection method, pulses are utilized to form a signal using the electric detection method. The test zone is directly connected to the built circuit, enabling the detection

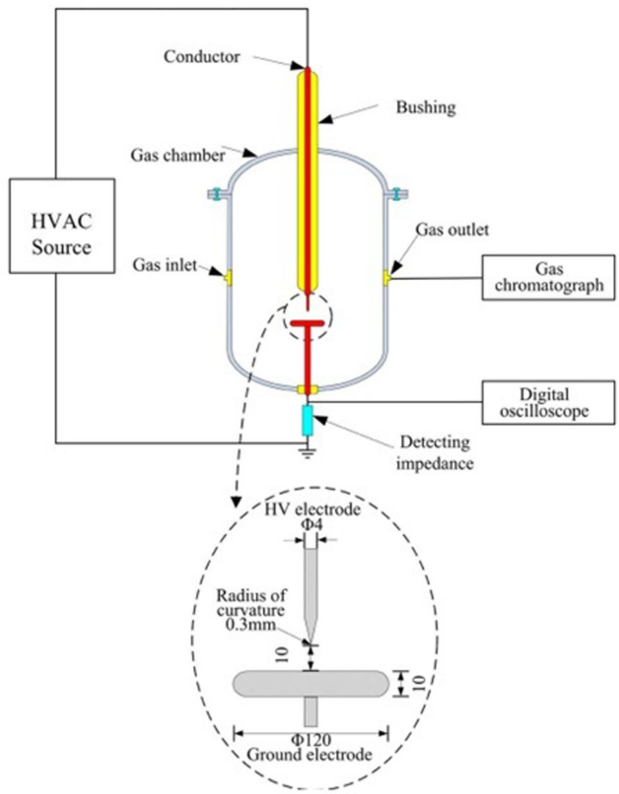


**Fig. 5** Schematic diagram of SF6 decomposition experiments (unit: millimeter) [68]

of the PD-indicating pulse of current [72]. Two international commissions that support this method are the International Electrotechnical Commission (IEC) and the Institute of Electrical and Electronics Engineers (IEEE) [73]. Figure 9a, b [1, 74] illustrates a general electrical detection technique for checking the state of the power transformer. Although online testing is susceptible to electromagnetic interference but sufficient for offline testing, further development of methods to identify PD activity is required [75, 76].

The key benefits of the electrical PD detection approach are its wide frequency range, excellent sensitivity, and ability to locate the PD cause. However, this method also has certain drawbacks, including the inability to conduct on-site testing, susceptibility to electromagnetic interference (EMI), and the presence of significant ambient noise [69, 77].

In Fig. 10, this circuit has several advantages when viewed from the perspective of external interference. However, calibration is somewhat challenging, involving balancing and synchronizing multiple devices.

Figure 11 illustrates that when high-voltage (HV) equipment in the form of a transformer is the part being tested for PD, the level of inductance complicates measurement, making it more complex, and the internal circuit is challenging. Connecting the transformer to the measuring equipment, i.e., via a capacitive bypass bushing, can solve this problem.

### 3.4 Electromagnetic (UHF) method

In some early studies, electromagnetic (EM) techniques demonstrated a linear correlation between the PD charge and the potential signal source at a specific PD position [78]. Conic, spiral, and Vivaldi antennas can be used as sensors in the detection of ultra-high-frequency (UHF) electromagnetic waves [79, 80]. UHF sensors are currently a notable research area being developed due to their uses, such as being unaffected by low-frequency signals, experiencing insignificant noise effects from the internal transformer construction through denoising and white noise removal techniques, and encountering corona-free pulse interference [81, 82].

Figure 12 illustrates a power transformer's circuit schematic, showing the effects of several PD types on its UHF calibration [83]. Various types of current transformers, including Rogowski coils, HFCT, and RFCT, have been extensively studied as sensors for PD detection [84–87].

This technique relies on identifying electromagnetic waves produced in transformers during PD incidents. Typically, PD in the transformer produces electromagnetic wave signals between 300 MHz and 3 GHz [88].

A diagram of the PD detection method on UHF is shown in Fig. 13. Here, an antenna sensor captures EM waves generated by the PD event on the transformer. The signals of PD must be amplified to a frequency range that the UHF sensor can detect because it is usually too weak to be detected by the sensor. Between the measurement system and the sensor is a connection to the amplifier. A filter is also attached between the sensor and the measuring apparatus to reduce outside noise [81]. This produces a PD electromagnetic signal.

Excellent ambient EMI sensitivity and immunity are additional features of this method, which are essential for on-site monitoring [89]. The fundamental problem with this approach is the lack of calibration procedures and the sensor's high sensitivity to electrical noise from radios, televisions, and other sources when placed externally [90, 91].

### 3.5 Acoustic emission method

The transformer's PD typically produces an auditory emission signal with a frequency range of 20 kHz to 1 MHz [92]. Acoustic sensors like piezoelectric, fiber optic, etc., can detect these acoustic waves as they travel through the transformer. The transformer tank can have this sensor placed either inside or outside of it. The speed of an acoustic sound wave is affected by the medium through which it passes. Echoes and signal reflections on the surface of the material also influence it. Therefore, the characteristics of the material are tested nondestructively by analyzing how these waves propagate through the supporting equipment of the transformer [70, 93]. Figure 14 shows the acoustic PD detection process for transformers.

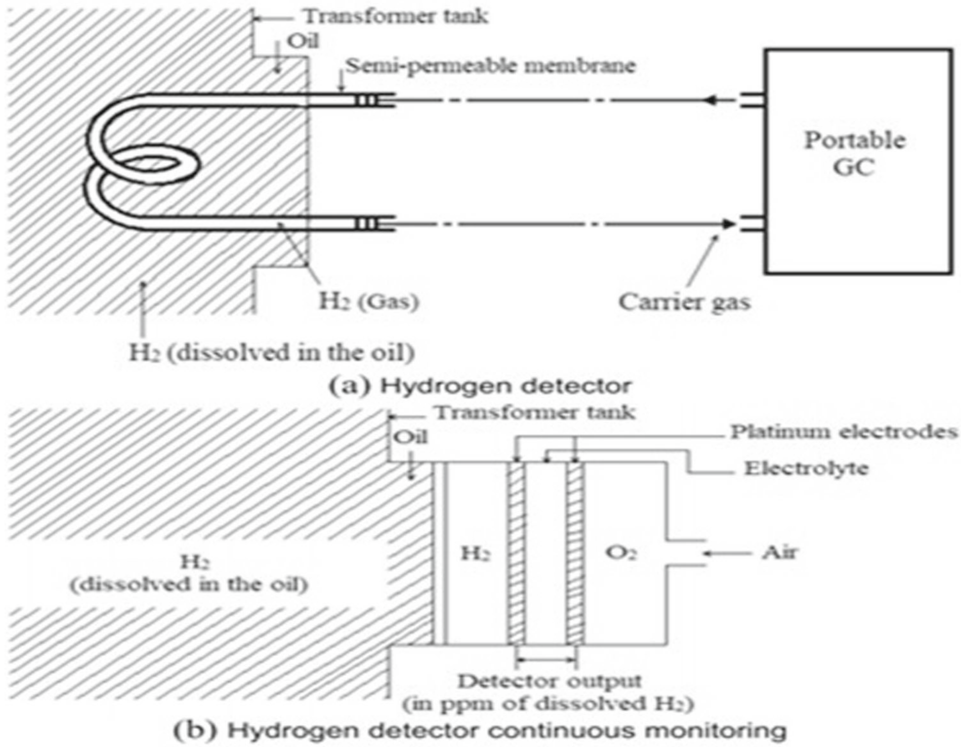


**Fig. 6** Method of Chemical PD Detection [69]

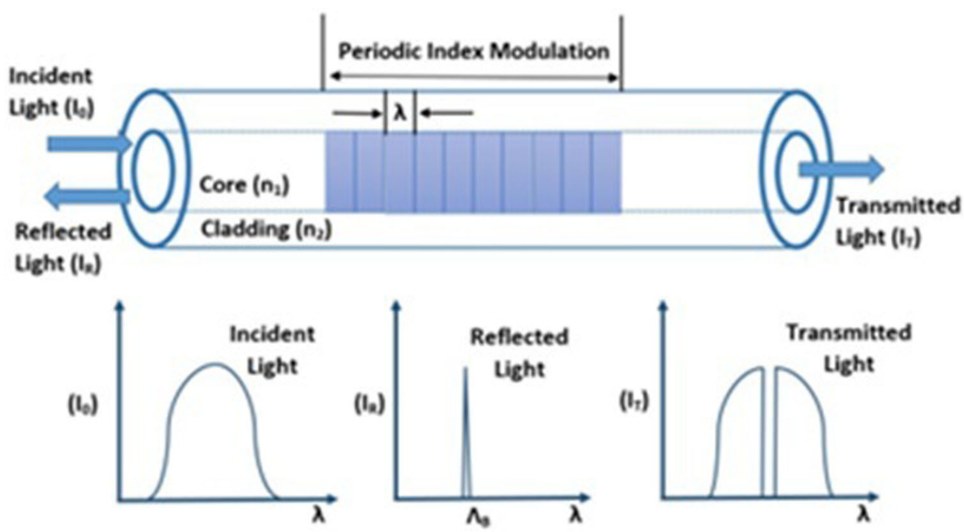


**Fig. 7** The operation of fiber Bragg grating sensors [22]

The acoustic emission method can determine the PD source's position compared to electrical and chemical methods. This method is also robust against the effect of EMI [69, 94]. For instance, the iron core and windings of a transformer cause wavefronts to be reflected and refracted as an acoustic pressure wave travels through them. The signal strength is diminished by the transformer's internal multipath sound wave propagation [93]. This technology has lower sensitivity than electrical engineering because of wave propagation reflections and echoes, resulting in a feeble received signal. The sensor must be highly responsive to even the tiniest fluctuations in signal amplitude to record PD [69].

### 3.6 Combinational method

A combination of AE and DGA methods has been attempted to find the disturbance position [95]. Using DGA and AE techniques together is similar to photo-acoustic spectroscopy (PAS). In Fig. 15, the use of PAS is shown [96]. Ultrasonic and UHF sensors have been combined in various ways to achieve good results in detecting discharge sources and can

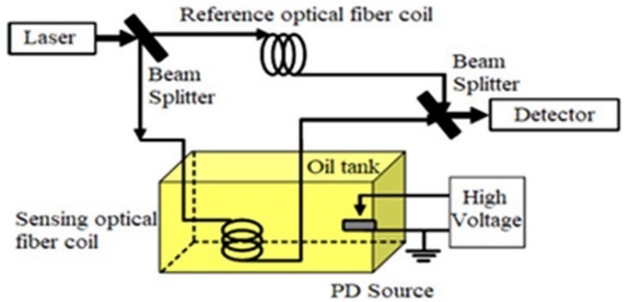


**Fig. 8** Optical PD detection method [70]

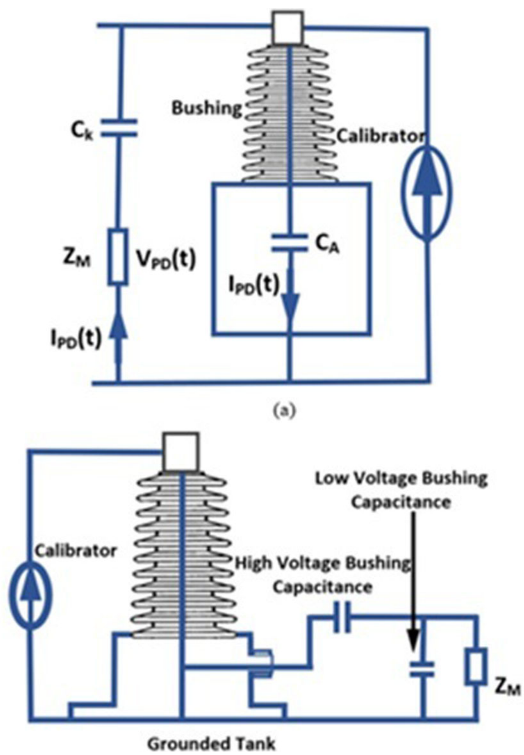


**Fig. 9** **a** IEC 60270-based indirect measurement circuit using external coupling capacitor. **b** Capacitor through bushing taps for coupling [1]

also utilize a combination of EM and acoustic techniques [97]. By comparing the AE sensor signal with the signal from the EE during the reference time of the discharge, it is possible to obtain a better result, ensuring that the detected signal is not noise in an inventive form [98].

A combination of several methods has been used to identify discharges, which are employed to determine the overall insulation failure of a transformer [99]. Combining AE and optical techniques ensures that the reference signal originates from the discharge source while using the other sensor as the AE sensor to determine the location of the PD [100]. A comprehensive comparison of the various discharge detection methods applied is presented in Table 1.

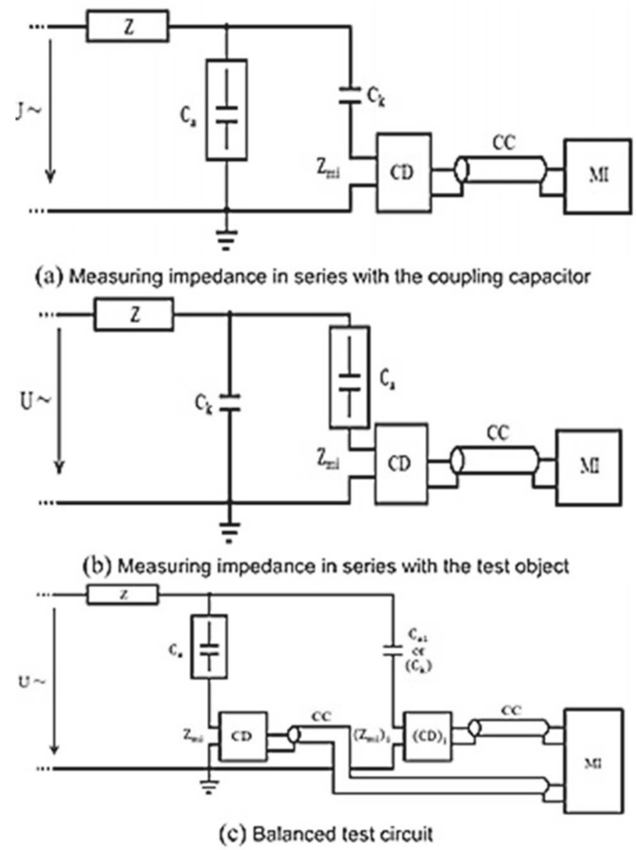


**Fig. 10** Basic circuit of the electrical PD detection according to IEC 60270 [1]

## 4 Diagnostic CD on high-voltage equipment

CD diagnostics is an effective way to categorize defects in high-voltage booths and switchgear equipment. The primary goals of CD diagnosis are to distinguish between different types of defects and to pinpoint the CD's underlying etiology. The diagnosis of CD is challenging because cubicle switchgear has a very intricate insulation scheme with nearly inaccessible internal components. Due to its tiny structure, online testing was only done on switchgear and cubicle terminals. Sophisticated testing equipment and knowledgeable staff are required to make a correct diagnosis.

The IEC 60270 standard states that electrical discharge measurement has excessive noise due to sensitivity limitations [101]. The cubicle-CD switchgear emits EM waves in the same frequency range as the UHF technique, with a high EM frequency range of 300 to 3000 MHz. Due to the environment's EM resistance, installation of the UHF sensor in the cubicle switchgear is possible even while it is in use and still allows for proper CD signal recognition. A piezoelectric sensor positioned on the cubicle-switchgear wall can perform CD localization; now, the acoustic signal arrives to record CD activity using EE or EM approaches. The issue is that

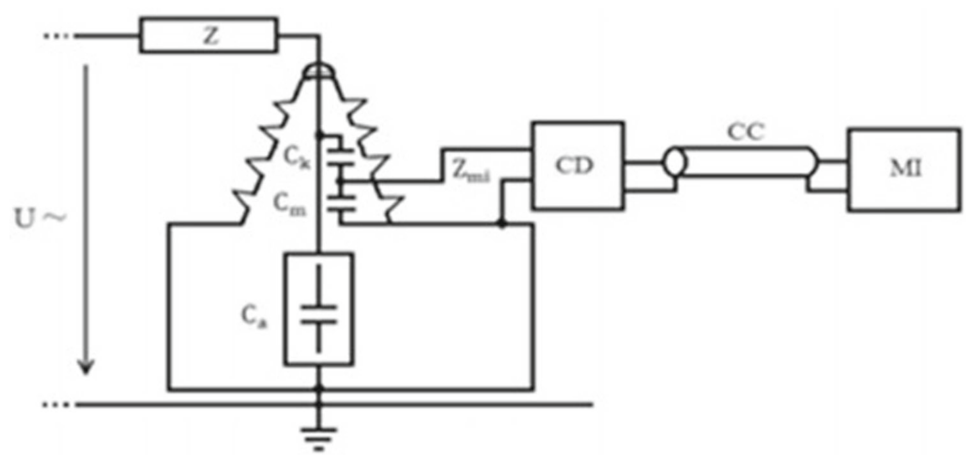


**Fig. 11** PD detection circuit by the capacitive bypass of the bushing [1]

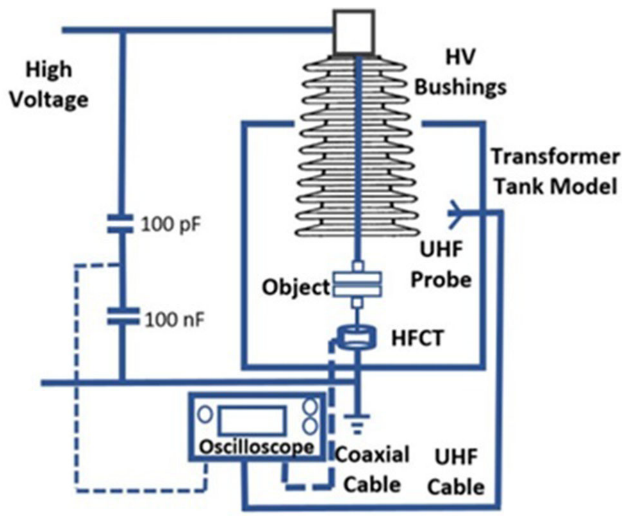


**Fig. 12** Circuit drawing for analyzing the PD effect [83]

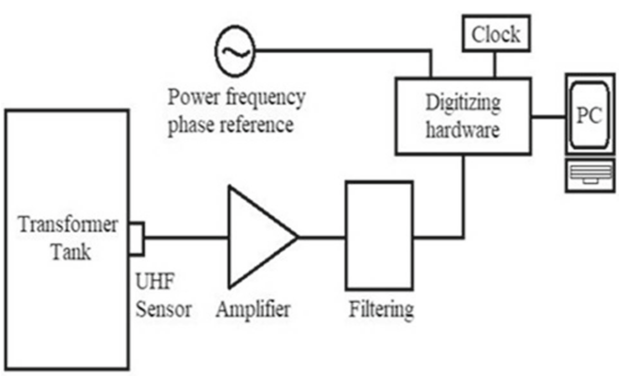


**Fig. 13** The UHF PD detection method block diagram [91]

the high-voltage equipment's intricate structure distorts the acoustic signal.

The EE discharge measurement system integrates the recharge current to determine the apparent charge level (in pC). In contrast, the EM discharge measurement system senses EM radiation through the UHF sensor to measure voltage (in mV) [102]. Given that the measurements were not made directly, the apparent charge (pC) in the factory acceptance test (FAT) is acceptable since the actual discharge value (pC/mV) could not be determined [103].

The sensitivity of electrical measurements can be increased by applying coupling or quadrupole capacitor effects. For that, it is essential to identify the antenna factor (AF) [104]. The gigahertz transverse electromagnetic (GTEM) cell is built with a coaxial cable that extends inside of it, and by isolating the device under test from external electromagnetic interference, a known electromagnetic field is introduced equipment under test (EUT). The first calibration step is the GTEM cell, which reflects the sensor effect. The transformer and UHF antenna are linked to assess the calibration sensitivity for measurement competency. A known UHF calibration impulse was initially introduced in [104] to calibrate the cable and measuring instrument. The calibrated path is then given audio frequency (AF) to add a sensor feature. AF can give various calibration points from the calibrator to the antenna in the transformer by inserting a transfer function with a frequency dependency specification. The calibration procedure can be sped up by applying the scalar correction factor AF, which accurately displays the discharge frequency. Since most power transformers were placed more than 40 years ago, online monitoring of transformers with diagnostics has become essential [105].

## 5 Monitoring using acoustic emission method

This study focuses on the description of the acoustic emission method presented in Table 2, where numerous discharge detection methods are demonstrated based on acoustic emission for high-voltage equipment. A brief explanation of the

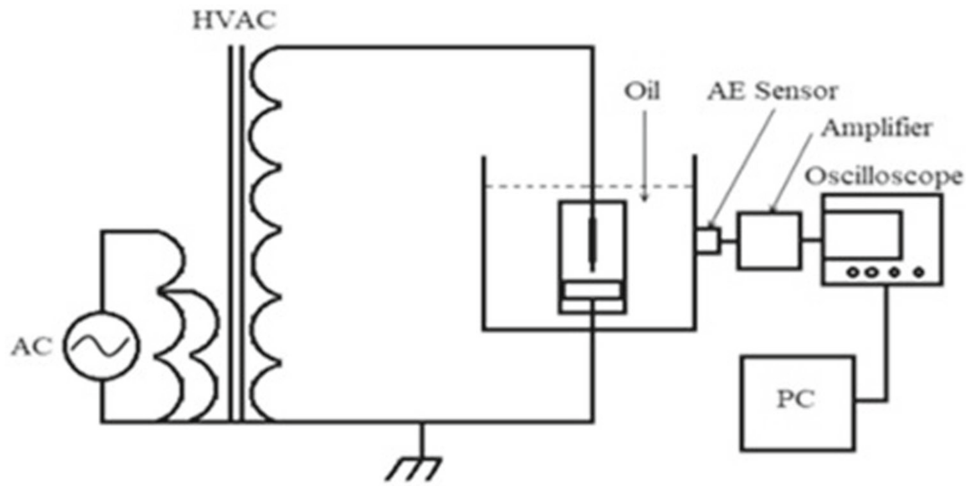


**Fig. 14** Oil-filled transformer acoustic PD detection method [69]

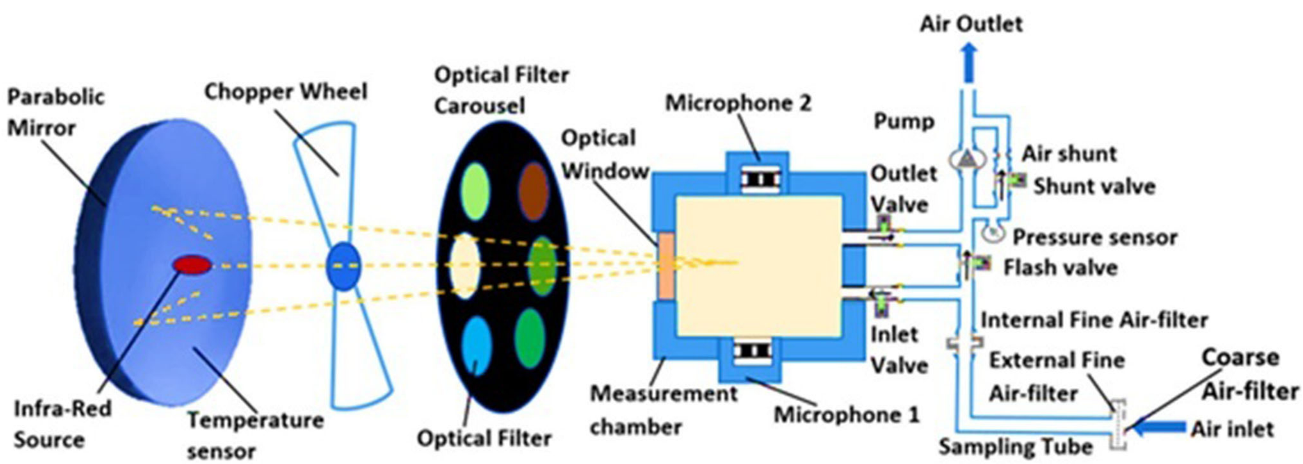


**Fig. 15** Spectroscopy-based photo-acoustic DGA system [96]

measurement method is given in this section. AE in power transformers can also occur mechanically due to oil evaporation close to the band, an electric arc, and mechanical vibration. The signal resembles a pressure wave and has distinct characteristics for different AE sources, such as frequency and amplitude variations [40].

The block diagram of the power transformer recording system for detecting the AE signal from the discharge is shown in Fig. 16. This system is used when the power transformer is operating normally. For many ultrasonic systems, the wideband piezoelectric transducer is a typical transduction component. To detect the AE signal, it is magnetically placed on the transformer tank. The AE signal is subsequently amplified, subjected to filtering, and sent to the AE analyzer for recording.

Multiple origins of discharge can be found using the AE approach. A microphone [106, 107], a piezoelectric sensor [108], an accelerometer [109], and a fiber optic (FO) sensor [110–112] are examples of AE detection devices. Due

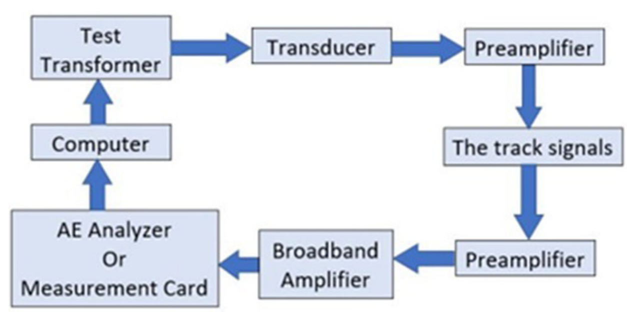


**Fig. 16** Recording system to detect AE Signals from PD [22]

to the signal's quick attenuation as it passes through different media, the fundamental flaw of the AE approach is the poor localization of the discharge source on the transformer winding [113].

Complex acoustic emission behavior, a low detectable signal strength, and a high cost are drawbacks of the AE technique. These AE detection methods are outperformed by fiber optic sensors due to their higher signal-to-noise

**Table 2** Comparison of acoustic emission methods for partial discharge detection monitoring

| Acoustic emission method | Advantages | Disadvantages | Key features |
|---|---|---|---|
| Microphone 106, 107] | - Highly sensitive to sound in low- to mid-frequency ranges<br>- Noninvasive and easy to implement<br>- Relatively inexpensive and widely available | - Less sensitive to high-frequency vibrations produced by PD<br>- Susceptible to background noise interference<br>- Limited detection range | - Detects airborne sound waves<br>- Typically used in environments with controlled noise |
| Piezoelectric sensor [108] | - Highly sensitive to mechanical vibrations caused by PD<br>- Wide frequency response, suitable for detecting different levels of PD activity | - Can be affected by mechanical noise from the surroundings<br>- Requires direct physical attachment to equipment (invasive) | - Converts mechanical vibrations into electrical signals<br>- Effective for detecting PD in environments with mild mechanical noise |
| Accelerometer [109] | - Accurate in detecting vibrations and acceleration changes in equipment<br>- Capable of monitoring vibrations from very low to very high frequencies | - Relatively expensive and requires a more complex setup<br>- Susceptible to interference from external vibrations not related to PD | - Measures acceleration changes due to PD activity<br>- Used to detect vibrations in stable mechanical conditions |
| Fiber optic sensor [110–112] | - Noninvasive and resistant to electromagnetic interference<br>- Capable of detecting small vibrations over a wide frequency range<br>- Can interact with remote monitoring technology | - Requires more expensive equipment and complex installation<br>- Sensitive to environmental changes such as temperature and pressure | - Uses changes in light in optical fibers to detect vibrations<br>- Very effective in heavy industrial environments full of electromagnetic interference<br>- In this context, although fiber optic sensors operate on optical principles, they can be used to detect acoustic waves generated by partial discharges, for example, through techniques such as fiber Bragg grating (FBG) or distributed acoustic sensing (DAS) |

ratio and wider auditory field detection (SNR). Multi-CD sources and noise resulting from the internal high-voltage equipment design can be found using denoising and optimization approaches.

The capacity to identify the discharge pressure wave and distinguish the resulting signal from background noise determines how accurate the acoustic discharge location approximation will be. To perform accurate discharge source analysis, a high-sensitivity sensor system is needed to detect acoustic waves at multiple transformer sites, and a reliable signal processing system is needed to correct the interpretation of the results [114].

# 6 Denoising techniques

The CD pulses are erratic, transient, and nonperiodic. The excess discharge impulse in the acquired CD signal captured by the CD sensor makes processing difficult. Signal processing methods must be used to segment the received signal further. Signal processing techniques are effective when considering several sources of CD generated at various isolations. Several signal-denoising algorithms have been widely used, such as artificial neural networks, matched filtering, empirical mode decomposition, and other methods [115–118]. The following is a description of some popular denoising methods.

## 6.1 Fast Fourier transform

The fast Fourier transform (FFT) method computes the discrete Fourier transform (DFT) [119], a mathematical technique that converts time-domain signals into their corresponding frequency components. While effective for stationary signals with small fluctuations, FFT has limitations in dealing with transient, nonperiodic signals such as those associated with partial discharge. The discharge signal exhibits erratic and irregular behavior, which is not well suited for FFT's assumptions of signal stability and periodicity. As a result, alternative methods, such as the wavelet transform, are often preferred for PD analysis [120]. Despite its limitations, FFT remains useful for analyzing frequency components in more stable environments or for initial signal segmentation.

### 6.2 Wavelet transform

The wavelet transform (WT) has gained widespread application in PD signal processing due to its ability to analyze both stationary and nonstationary signals. Unlike FFT, which transforms the entire signal into the frequency domain, the WT decomposes the signal into small wavelets that represent localized time–frequency information [121]. The WT is particularly well-suited for PD detection because it can isolate high-frequency discharge events while filtering out background noise. Its flexibility in time and frequency resolution makes it a powerful tool for real-time monitoring of PD activity [122]. This approach allows for better handling of transient, erratic signals such as PD by dividing the signal into frequency bands with wavelet coefficients. As a result, noise can be reduced more effectively while preserving critical features of the discharge signal [118].

### 6.3 Ensemble empirical mode decomposition

Ensemble empirical mode decomposition (EEMD) is a refinement of the traditional Empirical Mode Decomposition (EMD) method, which aims to extract intrinsic mode functions (IMF) from complex signals [117]. The Hilbert–Huang transform (HHT) consists of two parts: Hilbert spectrum analysis (HSA) and empirical mode decomposition (EMD). Although HHT is frequently employed in error analysis, it has limitations in the EMD technique, where issues occur due to problems with mixing modes during the sieving process. EEMD is a more accurate and robust noise-assisted analysis technique [123, 124].

The method is particularly useful for handling nonlinear and nonstationary signals, such as those produced by PD in high-voltage transformers. During signal processing, the IMF can capture subtle irregularities and rising waves associated with PD events, making it possible to isolate the discharge signal from background noise [125]. EEMD's ability to handle multicomponent signals at various frequencies makes it a valuable tool for improving PD detection accuracy in challenging environments.

### 6.4 Mathematical morphology

Mathematical morphology is a nonlinear signal processing method based on the application of morphological operators between the measured signal and predefined structural elements. This method is particularly effective for shape-based filtering of PD signals [126]. The structural elements are used to reshape the PD signal, enhancing certain features while filtering out noise. However, the method's reliance on repeated signal frequencies limits its applicability in environments where the signal structure is highly variable [127]. Despite this limitation, mathematical morphology can be useful in specific PD detection scenarios where the discharge signal exhibits regular patterns, making it easier to filter out unwanted noise.

### 6.5 Blind equalization

Blind equalization (BE) has the advantage of not requiring extensive analysis of the source signal, making it a versatile method for PD signal processing in complex environments. However, one major drawback is that BE typically requires more sensors than the number of discharge sources, which can complicate sensor deployment and increase costs. Chan et al. [118] proposed an automated BE technique specifically for PD signal processing in power transformers, demonstrating its effectiveness in extracting the source signal without the need for detailed source analysis. By reducing noise levels in the recovered PD signal, BE offers an efficient method for isolating the discharge signal in noisy environments.

### 6.6 Artificial neural network

Artificial neural networks (ANN) have gained considerable attention for their ability to perform complex signal processing tasks, including denoising of PD signals. The multilayer feed-forward neural network (MLPFNN) is one of the most used ANN architectures for this purpose [116]. The back-propagation algorithm is employed to update the weights of the input and output layers to optimize denoising performance. One of the key advantages of ANN-based denoising is its ability to improve accuracy by learning from data and adapting to signal variations. Increasing the number of hidden layer nodes enhances the network's ability to denoise complex PD signals, although this comes at the cost of increased processing time [128]. ANN techniques have proven highly effective for increasing the accuracy of PD detection, especially when combined with other signal processing methods [116, 129]. The adaptability and learning capability of ANN make it a powerful tool for real-time PD monitoring in high-voltage equipment.

### 6.7 Wiener filtering

Wiener filtering is a widely used denoising technique that operates by minimizing the mean square error between the estimated and the actual signal. It is particularly effective in reducing noise in signals that are corrupted by white

Gaussian noise. In partial discharge (PD) signal denoising, Wiener filtering proves valuable in recovering signals that have been significantly distorted due to environmental interference. This method works by adjusting the filter response based on both the signal and noise characteristics, making it adaptive and suitable for real-time PD monitoring applications.

Wiener filtering has been applied effectively in PD detection for high-voltage transformers, enhancing the clarity of measured signals while preserving the underlying PD event characteristics. For instance, studies such as [130, 131] have demonstrated the robustness of Wiener filters in isolating PD events from noise, particularly when dealing with transient and erratic signal patterns often found in PD monitoring. This filtering technique's ability to address complex noise conditions, such as those found in transformer insulation monitoring, makes it a highly effective method for increasing the signal-to-noise ratio (SNR) and improving diagnostic accuracy.

### 6.8 Least mean squares

The least mean squares (LMS) algorithm is a well-established adaptive filtering method used to minimize the mean square error in noisy signals. LMS works by iteratively adjusting the filter coefficients based on the error between the estimated output and the desired signal. In partial discharge (PD) detection, LMS is often employed to track and remove noise from signals obtained in high-voltage equipment, making it an effective tool for enhancing PD signal clarity, especially in real-time monitoring systems.

This method's adaptability and efficiency in real-time applications make it suitable for environments with fluctuating noise conditions, such as transformer insulation monitoring. LMS can handle both wideband and narrowband interference, which is common in PD signals. For instance, the application of LMS in cable system PD detection is detailed in studies like [132], which demonstrates the method's ability to improve PD signal accuracy by reducing signal distortions. The combination of LMS with other filtering methods, such as adaptive and wavelet filtering, further enhances its performance in denoising PD signals, making it a versatile and powerful approach for improving the signal-to-noise ratio (SNR) and detecting PD events effectively.

### 6.9 Singular value decomposition

Singular value decomposition (SVD) is an advanced matrix factorization technique widely used for noise reduction and signal processing. In partial discharge (PD) denoising, SVD has gained prominence due to its ability to separate noise from the underlying PD signal by decomposing the signal matrix into singular values and vectors. This method allows for the identification of the most significant components of the signal while filtering out the less significant, often noise-related, components.

SVD-based methods are highly effective in processing signals that are erratic and transient, as commonly found in PD signals. By isolating noise, SVD can enhance the accuracy of PD detection and improve the quality of the recovered signal. For example, in the study [133] an improved version of SVD combined with variational mode decomposition (VMD) is proposed, demonstrating enhanced performance in signal denoising. This hybrid approach preserves critical signal information while effectively removing noise, making it a powerful tool for PD signal processing. SVD's flexibility and robustness in handling complex, high-dimensional data make it an essential technique for modern denoising applications, especially in the context of high-voltage transformer monitoring.

### 6.10 Principal component analysis

Principal component analysis (PCA) is a powerful statistical technique used for dimensionality reduction, noise filtering, and feature extraction in signal processing. In the context of partial discharge (PD) detection, PCA is applied to analyze large datasets, reduce redundant information, and isolate the most relevant components of the PD signal. By projecting the data onto a set of orthogonal principal components, PCA effectively separates the noise from the useful signal, improving the accuracy of PD detection.

PCA has been successfully used in combination with other denoising techniques, such as the discrete wavelet transform (DWT), to enhance signal clarity. For example, in the study [134] the combination of DWT and PCA demonstrated significant improvements in identifying PD signals by filtering out noise while preserving key signal characteristics. This makes PCA a valuable tool in processing complex PD signals in high-voltage transformers, where noise can obscure critical diagnostic information. By focusing on the principal components of the signal, PCA enhances the signal-to-noise ratio, making it an effective method for real-time PD monitoring and fault detection.

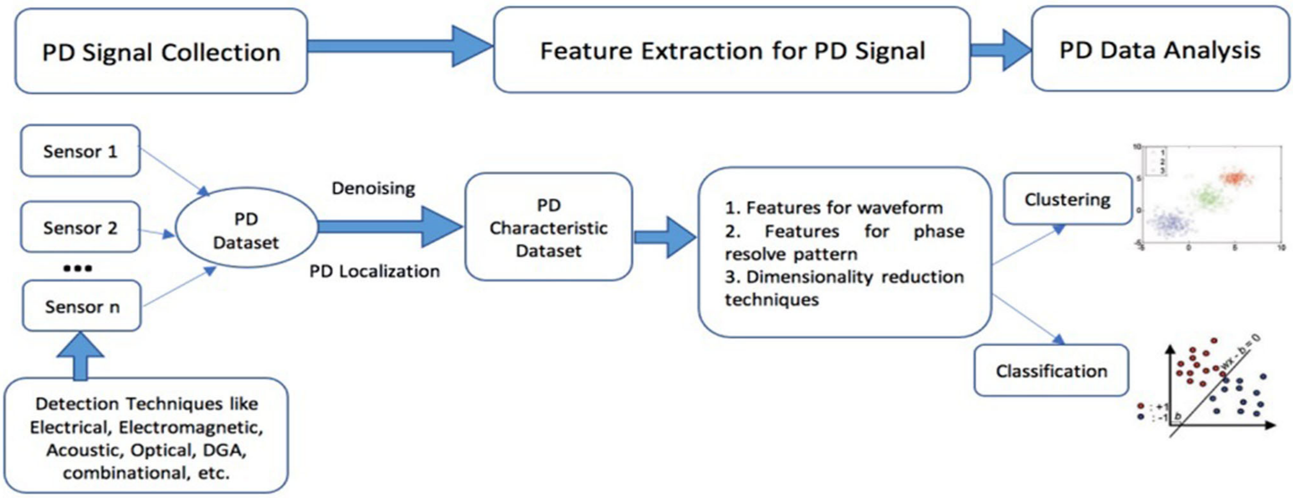


**Fig. 17** Diagram of the partial discharge monitoring system workflow [22]

### 6.11 Total variation denoising

Total variation denoising (TVD) is a robust method used to reduce noise while preserving important features of a signal, particularly its edges and abrupt changes, which are crucial in partial discharge (PD) signal processing. TVD works by minimizing the total variation of the signal, which helps to smooth the noisy components without significantly affecting the underlying PD signal. This method is particularly effective when dealing with transient signals that contain sharp discontinuities, such as those found in PD events.

In PD detection, TVD is often combined with other techniques like wavelet thresholding to enhance its denoising capabilities. For instance, the study [135] demonstrated how the combination of wavelet transform and total variation theory could effectively suppress noise while maintaining the integrity of the PD signal. This hybrid approach ensures that important diagnostic information is retained, making it suitable for applications in high-voltage transformer monitoring. The ability of TVD to handle signals with sharp transitions makes it a valuable tool for PD denoising, especially in environments where signal clarity is essential for accurate detection and fault diagnosis.

### 6.12 Nonlocal means

Nonlocal means (NLM) is an advanced denoising algorithm that reduces noise by averaging similar patches of a signal or image, even if they are spatially distant. This approach is particularly useful in partial discharge (PD) detection, where transient noise can obscure critical signal characteristics. NLM works by preserving important signal details while effectively eliminating random noise, making it suitable for environments with complex noise patterns.

In PD signal denoising, NLM has shown promising results when combined with other techniques like the complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN). For instance, the study [136] demonstrates how the NLM algorithm enhances the effectiveness of CEEMDAN by selectively filtering out noise based on the similarity between signal segments. This combination improves the clarity of PD signals, preserving crucial information for accurate fault detection. Moreover, NLM has also been applied in complex environments, such as in the study [137] where the method was used to denoise images for detecting faults in high-voltage systems. By maintaining key features and reducing noise, NLM proves to be a highly effective technique for PD signal processing and image-based anomaly detection.

## 7 Extraction of features from high-voltage equipment

Extracting multiple features is essential in analyzing discharge signals from high-voltage equipment. There have been many examples of feature extraction that are often done [25, 138]. The statistical overview of feature extraction in high-voltage equipment is the main topic of this section. A flow diagram of the partial discharge monitoring system is shown in Fig. 17. The monitoring system comprises three components: gathering discharge signals, extracting features from discharge signals, and analyzing discharge data. Two distinct patterns, PRPD and TRPD, can represent the filtered data after applying the discharge signal-denoising and localization procedure. High-dimensional data is frequently encountered when investigating discharge, necessitating dimensionality reduction techniques.

Several methods relate the phase angle, the number of discharge pulses, and the amplitude of the charge, which is then converted into positive and negative half cycles [139], two separate groups that characterize PRPD. The distribution's skewness, mean, variance, kurtosis, and Weibull statistical features can be derived [140]. The statistical feature has the benefit of taking less time to compute. This study includes statistical feature analysis for discharge signal extraction on transformer isolation flaws [141].

Discharge patterns were identified by Chen [142] in power transformers using a fractal-based feature extraction method, and the PRPD pattern is processed using an existing technique, namely the box-counting technique. Although scale fluctuations and promising surface roughness measures mean fractal dimensions are unaffected. The inability to distinguish between features of the same fractal surface value led to the creation of a new variable known as lacunarity [143].

The widest variance of the data is projected on the smaller dimensions to reduce space while increasing the desired sample spread [144]. The scree plot, a graph showing the size of the eigenvalues about their number, can be used to determine the number of primary components needed to determine the precise value of the actual data [141]. Furthermore, Rahman et al. [86] proved that principal component analysis (PCA) can autonomously localize discharge sources in transformer windings. Artificial neural networks (machine learning approaches) have now demonstrated respectable efficacy for the identification and recognition of discharge [145, 146]. Duan et al. [147] used four different fake discharge faults (air gap discharge, floating, surface, and bar plane) to identify discharge, which is comparable to the methodology for evaluating power transformers proposed in [148]. A sparse auto-encoder (SAE) technique is applied in deep learning for feature extraction. Deep learning techniques from SAE and SoftMax produce encouraging results with an accuracy higher than 96%.

## 8 Classification in high-voltage equipment

This specific classifier is required because hesitancy could result in incorrectly classifying the discharge model. Additionally, the features derived from the discharge pattern determine the discharge accuracy classification.

The initialization of an ANN is done using weights with modest values, and training is conducted using a forward and backward method [149]. The hidden layer attribute is employed to extract discharge characteristics. Li et al. [150] proposed a convolutional neural network (CNN) architecture to recognize the source of the discharge pattern of the UHF signal, shown in Fig. 18. The short-time Fourier transform (STFT) produces a $1 \times 128 \times 256$ input for CNN. The filter, pooling, and dropout layers comprise the algorithm's first three hidden layers.

Adaptive neuro-fuzzy inference system (ANFIS) is employed to eliminate the need to select a suitable fuzzy network for operation [151]. ANFIS is an effective method by combining unique If–then rules to identify PD patterns based on Sugeno's fuzzy model [152]. The input variable is set between 0 and 1 to improve training efficacy. With a 98% accuracy rate, it was found that the ANFIS model is superior to the fuzzy model when applied to detect discharge errors using dissolved gas analysis (DGA) [153].

Support vector machine (SVM) is a statistical-based regulation manager that uses basic algorithms and kernel functions [154]. In this method, discharge pattern data can be characterized using vector dimensions, depending on the quantity of input characteristics. SVM works well when nonlinearity, limited sample sizes, and big dimensions are factors [155]. Another tool to address nonlinear problem analysis inefficiencies is the kernel method. The authors in [156] classify discharge patterns based on SVM, obtaining favorable results even though the amount of data is very complex.

The decision tree approach utilizes internal nodes for feature testing, where leaf nodes represent class labels and routes between roots and leaves represent classification rules [157]. Because this method, unlike SVM or ANN, offers visible rules for discharge classification, it has been widely employed in discharge classification under various discharge situations.

A decision tree has determined power transformer cavity sizes and different discharge sources [158]. A straightforward and nonparametric approach called K-nearest neighbor (KNN) categorizes the training set by identifying the group of k items closest to the test object and assigning a type based on the correlation of their respective classes in the surrounding environment [159]. The labeled object, the number of nearest neighbors, and the constant "k" are the three main components of KNN. The KNN classification focuses on fresh data points according to a higher vote for nearby data points.

## 9 Clustering in high-voltage equipment

Data is grouped into clusters using the unsupervised learning process known as discharge signal clustering, where each cluster's components are closely related. In PRPD and TRPD, the clustering technique is frequently utilized to distinguish and organize discharge pulse characteristics from various discharge sources. The most recent discharge analyses in high-voltage equipment are shown in Table 3.

The K-means (KM) algorithm is a fast and easy centroid-based clustering method. K-means grouping is employed until the assignment and convergence stages are reached, allowing updates to be achieved [175]. This method poses

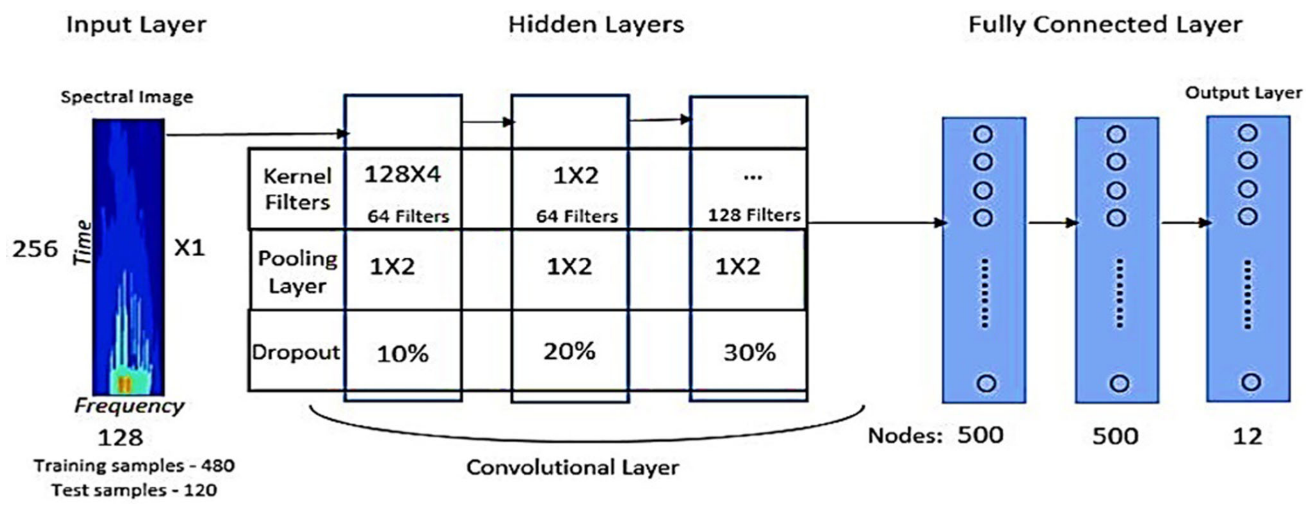


**Fig. 18** PD categorization with convolutional neural networks [150]

challenges due to limited knowledge and limitations such as local minimum convergence and fixed K values [176].

In hierarchical cluster analysis, clusters are formed using a clustering method known as the dominant order [177]. The basic assumption in agglomerative hierarchical clustering is that objects belong to discrete groups. Individual clusters are then joined based on the separation between the two objects, and the process is repeated until conditions are met. Divisional clustering initially allocates all objects to a single cluster, which is then divided into other clusters according to rules [178]. The hierarchical cluster analysis method can effectively study large structures, even though processing takes longer. Additionally, changes take time to appear once split or merge decisions have been made.

## 10 Challenges and future prospects

The resolution and sensitivity of sensor devices need improvement. For instance, although acoustic emission sensors have made significant and promising advances in high-voltage equipment for corona discharge detection, there are critical issues and potential solutions:

1. Study sensor design development thoroughly.
2. Acoustic emission sensors with high instrument sensitivity are generally required. Therefore, creating AE sensors for high-voltage equipment that can operate in any environment and at any temperature is challenging.
3. Investigate the creation of a multipurpose AE sensor that can be used in conjunction with other techniques to locate corona discharges (CD).
4. Study competent methods and techniques in signal processing, especially in signal denoising.

The main challenge is to create a multipurpose AE sensor system that can detect several CD characteristics simultaneously.

## 11 Conclusion and discussion

This review study thoroughly analyzes current methods for high-voltage equipment corona discharge signal analysis, covering feature representation, classification, and clustering strategies for discharge detection, localization, and error severity analysis. Different approaches to corona discharge detection collaboration have been introduced. The importance of detecting corona discharge in high-voltage equipment cannot be overstated, as the power system network depends entirely on uninterrupted operation.

This review study also discusses partial and corona discharges in high-voltage equipment and various flaws. Electric and nonelectric discharge detection methods of many types have been explored, along with the benefits and drawbacks of each method. There has been extensive discussion on the importance of discharge analysis in high-voltage equipment to determine the specific type of discharge damage. The corona discharge monitoring system comprises various processes for analyzing flaws, including feature extraction, clustering, classification, and CD detection. Every stage has been detailed, accompanied by suggestions for contemporary techniques.

Online CD measurement in high-voltage equipment is an effective method for analysis due to the complicated structure of high-voltage equipment and the constraints posed by on-site noise. Detection techniques can be further researched to identify symptoms and mitigate the significant impact of some noise on online sensing.

**Table 3** Latest development in discharge analysis in high-voltage equipment

| References, Year | PD Issues | Method | Feature extraction | Classification | Conclusion |
|---|---|---|---|---|---|
| [160], 2011 | Conductor particles of different sizes in transformer oil | Circuit created for PD assessments | Using the particle swarm optimization method | SVM stands for support vector machine | May be used to assess PD recognition online efficiently |
| [161], 2012 | – | Each oil valve has three UHF probes attached, and the exterior tank has piezoelectric sensors | Statistic evaluation | – | This technique works well for triggering the PD signal |
| [162], 2012 | Various types of discharges | Fractal UHF Hilbert for online | – | – | Successfully for recognizing PDs and for detection online UHF PD |
| [163], 2014 | Metal floating in the void, combined | Utilizing a spectrum analyzer and oscilloscope, UHF detection and recording | Denoising, wavelets, and db2 and sym2 | Forward-looking ANN | Classification and accurate identification of both single- and multi-PD phenomena |
| [164], 2014 | Surface discharge in insulation made of oil paper | Checking the model's voltage continuously in the lab | Spectrum (3 D) | Euclidean distance clustering | Demonstrates the "hold together" property of wavelet moments |
| [165], 2014 | Surface and interior discharges of the corona | Acoustic emissions are combined with numerous piezoelectric and fiber optic | Denoising | Algorithms for 3D localization based on lookup tables | Detection and localization of AE produced |
| [166], 2015 | There are various types of causes of partial discharge | Method of acoustic emission | Wavelet decomposition, the discrete Fourier transform, and PCA | K-nearest neighbor, SVM, quadratic discriminant analysis, and polynomial classifier | High-frequency AE sensors operating between 100 and 450 kHz were effective at detecting a variety of PD sources |
| [167], 2015 | Artificial PD defect | By putting in several new UHF antennas, UHF detection | – | – | Increased distinction between probable PD locations inside the transformer for improved PD localization accuracy |
| [168], 2015 | Surface, corona, and pressboard cavity discharges as well as surface and oil/air interface discharges | Analysis of two-dimensional linear discriminants (2DLDA) | TD-MFW-2DLDA, or two-directional modified fuzzy weights | SVM and fuzzy C-means | PD pattern identification is eliminated by TD-MFW-2DLDA |
| [169], 2016 | Various types of partial discharges | Combine PD detection | – | – | The capacity to distinguish the distinctive signals |

**Table 3** (continued)

| References, Year | PD Issues | Method | Feature extraction | Classification | Conclusion |
|---|---|---|---|---|---|
| [170], 2016 | Scratch on the insulation around the windings, an oil bubble, etc | Test system for measuring PD | Texture and statistical features | SVM | When the various sorts of flaws are categorized, texture features exhibit the highest degree of accuracy |
| [66], 2017 | Electrode point-plane | Acoustic emission-based localization | Source-filter model | | 1 cm localization accuracy |
| [171], 2018 | Model of a needle-plane | A oil-filtered of three-phase transformer | – | – | The attenuation rate of the EM signal decreases nonlinearly |
| [172], 2018 | Electroplate needle | Fiber optic sensor array and sound source localization | – | – | Better prediction than the traditional sensor |
| [173], 2019 | Transformer insulation paper water content | Sensor of optical fiber | – | – | Compatible with water activity probes in various dielectric oils |
| [174], 2019 | Surface, floating, and void electrode | – | Algorithm for discrimination | Maximum likelihood density-based spatial clustering | The multi-step discrimination approach |
| [147], 2019 | Deep learning-based identification of partial discharge defects | To obtain the PD current waveform and the detecting pulse current and ultra-high frequency | Demonstrating the viability of identifying the PD current waveform | The network's hyper-parameters | Which is a significant improvement over the conventional identification method |
| [67], 2021 | Sensitivity to time delay errors and solution complexity | PD localization method | The nonlinear localization equation is converted into a linear localization equation by eliminating the second order term | The optimal PD coordinates | Improve PD localization accuracy in transformers |
| [46], 2021 | DNNs are widely | Evaluate various electrical apparatuses and achieve high classification accuracy | The proposed model was verified by PRPD experiments UHF PD measurement systems | Classification problems of unknown classes using PDs in GIS and propose a deep ensemble model | Proposed model achieves better unknown detection performance |
| [61], 2022 | The RF-based monitoring system detects PD sources | Arrival time (AT) of the impulsive RF signal | The AT's automatic labeling in the RF PD signal using Bi-LSTM network applied on the CWT signal | The behavior of the radiated RF signals is influenced | The improved from the combination |
| [62], 2022 | Triggers PD in material defects | To identify and categorize PDs coming from multilevel PWM, suggest a machine learning | PD classification uses the greatest PD amplitude, length, time interval | PD classification uses the greatest PD amplitude, length, time interval | On test data, trained classifiers produced average classification accuracy scores of 95.3% and 98.5%, respectively |

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## Declarations

**Conflict of interest** The authors declare no competing interests.

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