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Overview and Partial Discharge Analysis of Power Transformers: A Literature Review

MD Rashid Hussain[1], Member IEEE, Shady S. Refaat[2], Senior Member IEEE and Haitham Abu-Rub[2], Fellow, IEEE

[1]Department of Electrical Engineering, Qatar University, Doha, Qatar
[2]Department of Computer & Electrical Engineering, Texas A&M University, Doha, Qatar

Corresponding author: MD Rashid Hussain (e-mail: md_rashid.hussain@qatar.tamu.edu).

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ABSTRACT The high voltage power transformer is the critical element of the power system, which requires continuous monitoring to prevent sudden catastrophic failures and to ensure an uninterrupted power supply. The most common failures in the transformer are due to partial discharge (PD) in electrical insulations which are the results of the insulation degradation over time. Different approaches have been proposed to monitor, detect, and locate the partial discharge in power transformers. This paper reviews and evaluates the current state-of-the-art methods for PD detection and localization techniques, and methodologies in power transformers. Detailed comparisons of PD detection techniques have been identified and discussed in this paper. The drawbacks and challenges of different partial discharge measurement techniques have been elaborated. Finally, brief reviews of PD denoising signals, feature extraction of PD signals, and classification of partial discharge sources have been addressed.

INDEX TERMS Power transformer, partial discharge, condition monitoring, fault diagnosis, feature extraction.

I. INTRODUCTION

The power transformers are the utmost fundamental part of the power system utilities [1]. The performance and constancy of the power system utilities are directly dependent on the power transformer [2]. Therefore, its health is essential for the power system's stability and reliability. Any failure may result in high capital loss with disruption of power supply [3]. The power transformers are exposed to different stress conditions in the form of electrical, mechanical, environmental, and thermal stress. These stresses are potential sources for different internal and external faults in the power transformer. The majority of these faults occur due to the impending deterioration of the insulation system [2]. To avoid the electric supply disruption, condition monitoring is performed. Monitoring is a form of predictive maintenance that determines the operating state and the assessment of the functionality of the power transformer. This helps in preventing possible failures by taking early action through scheduling maintenance tasks. [4].

The power transformer during the stage of operation may undergo various types of faults with different levels of severity [5]. Therefore, proper examination for detecting the transformer's health level is essential for the continuous operation of the electrical utilities. The condition monitoring systems of a power transformer can be classified into two main categories; online and offline. The online condition monitoring methods are preferred over offline methods even though the reliability of offline testing is higher [2]. Offline condition monitoring methods are usually performed during the manufacturing phase of the power transformer to examine the manufacturing defects, which are present in the form of voids, cracks, and bubbles in the insulation [6]. Offline testing methods include advanced electrical measurements, which are efficient enough to examine the PD activities. However, offline monitoring lacks the actual electrical and thermal conditions of the insulations that are different during the operating phase of the transformer [7].

The power transformer is a complex structure experiencing faults, which are categorized into internal and external faults. Fig. 1 shows the classification of fault in the power transformer [8]. Global statistics show that 70% - 80% of transformer's faults are internal faults [9]. The initiation of internal fault starts with the trivial discharge inside the transformer insulation, which is a transient state. Further, the trivial value of the discharge in the insulation can grow rapidly and lead to a complete breakdown. Internal faults arise due to fault in different areas which include the winding (axial displacement, buckling deformation, disc space

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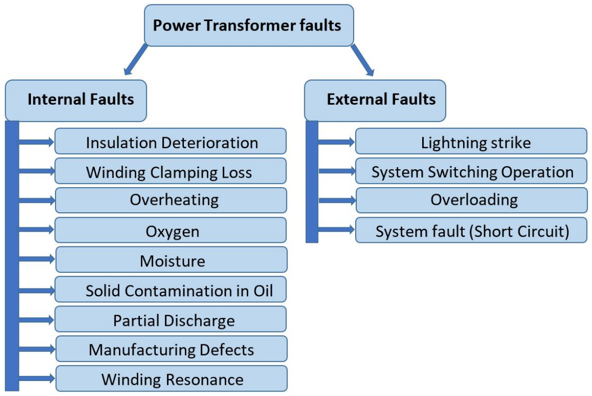

FIGURE 1. Classification of fault in power transformer.

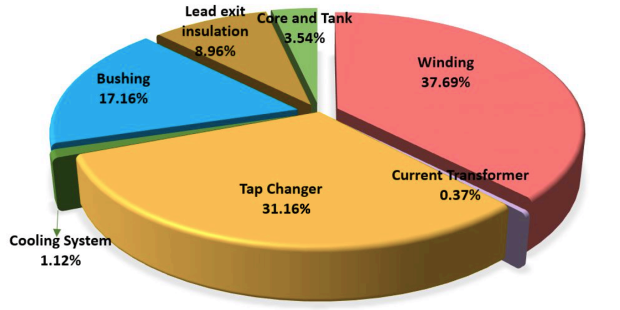

FIGURE 2. Transformer failure for transformer at substation (>100 kV) [15].

variation, and short circuit turns) [10], tank, insulating oil (oxidation, water penetration, dissolution due to temperature rise, and acidity) [11], core (core insulation failure, shorted lamination) [12], terminal (open leads, loose connections, short circuits) [13], cooling system, and tap changer (mechanical, electrical, short circuit, overheating) [14]. External faults occur due to several reasons including the external short-circuit of the power system, overflux, and overload. Fig. 2 shows different areas of fault location for transformer which are located in the substation (> 100 kV) [15].

The power transformer fault detection and condition monitoring are crucial to increase the electric system reliability. Several common online condition monitoring techniques are used. These include dissolved gas analysis (DGA) [16]-[17], partial discharge measurement [18], power factor measurement [19], frequency response analysis (FRA) [11], vibration and acoustic analysis [20], dielectric spectroscopy [21], differential protection [22], transformation ratio [23], and insulation resistance [24]. Among these techniques, partial discharge monitoring can effectively diagnose the transformer's condition with the possibility of advancement in the future.

PD is contemplated as the root cause of the insulation degradation where a complete breakdown can lead to transformer failure [25], [26]. Different PD analysis techniques for condition monitoring are performed for PD detection, identification, and diagnosis [27]. Several techniques were developed to detect PD including electrical detection [28]–[32], electromagnetic detection [26], [33]–[37], optical detection [38]–[40], acoustic detection [41]–[45], gas presence detection[16], [46]–[48], and combinational methods [41], [49], [50]. PD sources signals are received through a detector and are further analyzed to identify the locations and severity of insulation defects. The complex geometry of power transformers with different noise sources becomes quite challenging to identify the severity of PD defects and localization. The external noises are in the form of natural sources such as electrical storms, electrostatic interference, electromagnetic interference (through current cables), radiofrequency interference (from radio signals), and cross talk (cables separated by small distance). Whereas, the internal noises are mainly caused by the vibrations of the transformer core and windings. The PD detection system is desired to precisely identify the severity and locate the defects. The detection system process includes the denoising process of PD activity, feature extraction, PD classification, and PD clustering methods.

The main contributions of this paper are as follows:

- A brief description of the power transformer, its advances, and design for the improved insulation.
- Review of state-of-the-art techniques of power transformer faults, with a focus on various power transformer PD forms types, detection, and measurement in power transformer during the operating state.
- A comprehensive insight into various PD diagnostics techniques for different types of defects in power transformer during operation.
- Further, the common techniques for denoising, feature extraction, classification, clustering of PD data for localization, and severity of PD source with current advancement have been discussed.

The paper is organized as follows. Section II introduces partial discharge in the transformer. Section III provides PD detection techniques for the transformer. Section IV gives the most efficient PD diagnostics techniques used in the power transformer. The information regarding different denoising techniques is discussed in Section V. PD feature extraction, PD classification, and PD clustering are comprehensively discussed in Section VI, VII, and VIII, respectively. Finally, section IX concludes the paper.

II. PARTIAL DISCHARGE IN POWER TRANSFORMERS

PD is the electrical breakdown in the insulation that does not completely bridge the electrodes resulting in localized electric stress. This process is a slow insulation degradation and reducing the insulation life of the power transformer [51]. PD arises when there is a higher electric field than the threshold value causing a partial breakdown of the surrounding medium [52]. The transient behavior of the PD has the property of pulsating currents of duration between nanoseconds to microseconds [53]. PD discharge level

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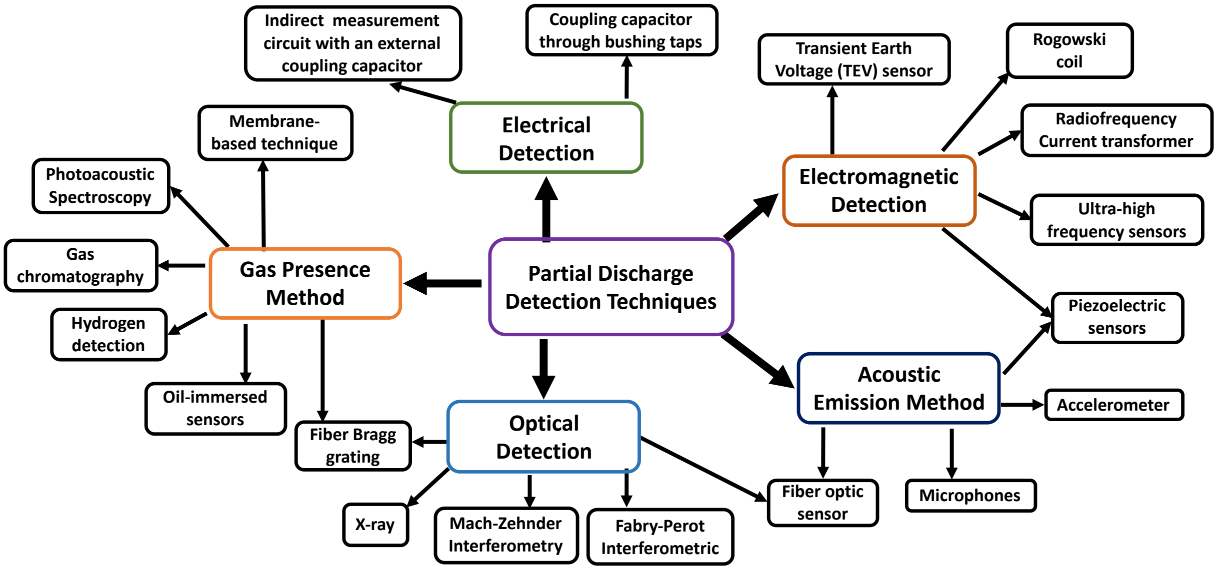

FIGURE 3. **Partial Discharge detection techniques**

cannot always justify the severity due to the possibility of rapid treeing phenomena. In general, the complete breakdown destroys the insulator, which does not retain any information regarding PD type [53]. Therefore, it requires continuous monitoring to resolve the issues in the early stage [54], [55]. Each type of defect has its distinguished degradation properties whose PD pattern can be used to figure out the insulation condition [56].

PD phenomenon has a stochastic behavior due to the unpredictable nature of pulsating PD occurrences. Some steps of the PD phenomenon can be predicted statistically, but not accurately due to its complexity. PD pulse properties such as amplitude, shape, and time of occurrence can examine PD phenomena keeping into consideration their random behavior. Stochastic behavior of PD can be due to the probability of introduction of the initial electrons, region of electric field strength, development of discharge in defects, ion space charge generation rate, variation in the gas constitution and density, the existence of ionizing radiation, and formation of PD pulse from the remainder of previous PD pulse [57].

Partial discharge in a power transformer can be categorized into five types: internal discharge, surface discharge, corona discharge, electrical treeing, and barrier discharge [58]. Internal discharge occurs due to the formation of cavities inside the insulator during the manufacturing process or due to aging. Also, due to higher voltage/electric stress in the cavities as compared to the surrounding medium. PD occurs if the voltage stress inside the cavity is higher than the inception voltage. Surface discharge starts at the high electric field region and then propagates to the lower stress region. The main cause of the surface discharge is due to the fact that dielectric strength at the interface of the insulations is less than the insulation. The surface discharge may occur is different areas which includes the cable terminal, bushings, line-insulator surface. Corona discharge can occur at the sharp conducting points, high voltage bare conductors, and even sharp points at ground potential in air and transformer oil. Electrical treeing may occur at a high electric field region inside the dielectric material due to defects in the form of a gaseous void, sharp electrode-edge, or metallic particle. The voids under high electric stress generate by-products (ultra-violet light and ozone gas) that decompose the insulator and produce new voids. The process of voids generation is repeated, creating weak points and form the electrical tree that finally leads to the breakdown. Electrical treeing can also be formed on the surface of the dielectric under high electric field stress due to contamination which causes flashover on the surface. Dielectric barrier discharge generally occurs due to the presence of insulators (generally silica, silica glass, ceramics, etc.) between the electrode pair [58].

The occurrence possibilities of PDs in the power transformer can be lowered by better design of the insulation system, reducing manufacturing defects in the drying, and impregnation process. Complete elimination of cavities in the insulation system is an impossible task since an ideal insulator cannot be manufactured.

Different types of defects causing PD can be present within the power transformer oil-paper insulation. The defects are (a) voids formation due to the separation of layers of paper wrapping the windings, where oil impregnation is absent. (b) Moving metallic particles in the insulating oil due to the aging process of metallic tanks and manufacturing flaws. (c) Voids formation in the bushings due to environmental effects, humidity, and surge voltage (d) Gas bubbles in the insulating oil due to aging, impurities in oil, and trapped moisture. (e) Trapped moisture in solid insulation during the manufacturing process. (f) The localized static electric charge due to the flow of oil, and the increase of the electric field resulting in the initiation of PD. (g) Tracking in solid insulation [59].

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Different physical and chemical processes in defects of the insulation system provide the foundation for PD monitoring techniques. PD investigation started in the 1960s, and for a decade, the research was performed to study void discharge phenomena [60]. Further, in the late 1970s satisfactory advancement took place towards distinct PD mechanisms such as treeing, flashover, sparks, avalanche, and streamers. [61]–[63]. The physical events occurring due to PD in the insulation systems of the power transformer are [64]: (a) Generation of mechanical vibrations results in the creation of acoustic waves in the ultrasonic region. (b) Emission of electromagnetic waves in the ultra-high frequency (UHF) region. (c) Ozone and nitrogen-based oxide formation due to a chemical reaction. (d) Emission of thermal and light energy [64].
Recently, data analytics and sensing technology are creating possibilities for the advancement of the auto-detection of PDs through PD monitoring systems [65]–[67]. A typical PD monitoring system comprises a PD signal collection unit, a feature extraction unit, and a data analysis unit. PD signal collection unit encompasses sensors designed to sense the physical phenomena of PD, which emits energy of different kinds. PD signals from the detectors can be represented into two different patterns, which are termed as time-resolved partial discharge pattern (TRPD) and phase-resolved partial discharge pattern (PRPD [68]. PRPD represents the φ- q-n waveform pattern, where φ, q, and n are the PD pulse phase angle, the amplitude of the apparent charge or discharge voltage, and the number of pulses, respectively. TRPD signifies the q-t waveform, where 't' is the time of the waveform and 'q' is the same parameter as of PRPD. PRPD's most common illustration is the phase window method, which splits the power cycle angle of 360° into a smaller phase window for feature generation [69]. The feature extraction for the PD signals unit extracts the momentous qualities (features) from the raw data [70]. Further, these features are used in the PD data analysis unit, which is generally furnished with pattern recognition methods such as artificial neural network, fuzzy clustering, and expert system for distinguishing PD from noise or source of PD and its location [71]- [72].

III. PD DETECTION TECHNIQUES

PDs consist of different physical phenomena having distinguished characteristics mainly electromagnetic waves, current pulses, heat, vibrations, and acoustic waves. [73]–[76]. PD detections and measurements are feasible due to the distinguished physical phenomena, which can be allotted into two groups: electrical and non-electrical methods. Fig. 3 shows different types of PD detection techniques for power transformers. This section provides a brief description of the measurement techniques.

A. ELECTRICAL (EE) DETECTION METHOD

EE detection methods apply the current pulse generated signal detection method. The circuit is directly connected to the testing region where PD activity is present and the current

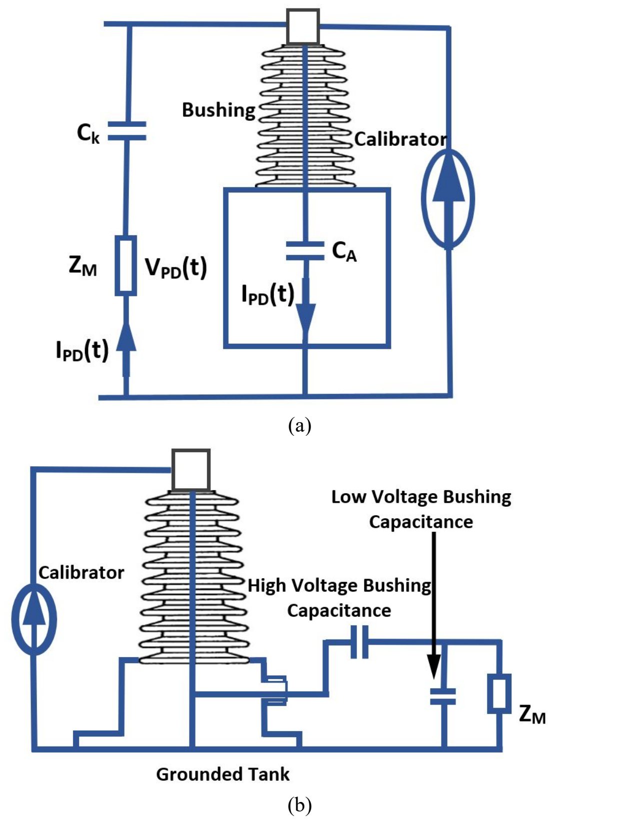

FIGURE 4. (a) IEC 60270 based indirect measurement circuit using external coupling capacitor. (b) Coupling capacitor through bushing taps [80].

pulse is detected [77]. The International Electrical and Electronics Engineers (IEEE) and the International Electrotechnical Commission (IEC) adopt this method [78]. When using this method, the level of charge due to PD is calculated to identify the condition level of insulation. The International Council on Large Electric Systems (CIGRE) proposed surveying the available detection systems for PD in power transformers [79]. The common electrical detection approaches used for condition monitoring of power transformers are indirect measurement circuit with external coupling capacitor and coupling capacitor through bushing taps, as shown in Figs. 4(a) and 4(b) [80], [81]. In Fig. 4(a), the indirect measurement test is performed, where the coupling capacitor (C_k) is kept in a parallel configuration with the tested insulation system capacitance (C_A). The apparent charge is calculated by the PD measurement device attached to the measuring impedance (Z_M).
For online testing, this method is not used due to a bulky high voltage coupling capacitor. But, if the bushings tap is available on the power transformer, as shown in Fig. 4(b), online testing can be conducted. Currently, the development methods are not efficient enough to locate the PD activities as online testing is prone to electromagnetic interference but is sufficient for offline testing (eg. routine tests of manufactured products or pre-commissioning routine tests) [82], [83]. Nevertheless, this method provides indications of the proper understanding of the insulation condition.

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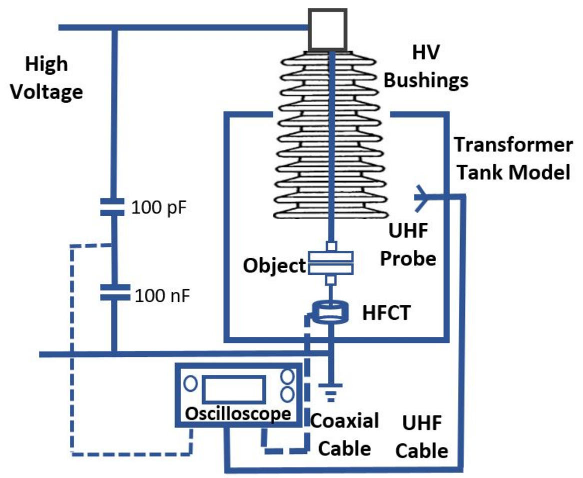

FIGURE 5. **Circuit diagram to examine the impact of different types of PD on UHF calibration in power transformer** [89]**.**

B. ELECTROMAGNETIC DETECTION METHOD

The electromagnetic (EM) method during the initial investigation showed that at a fixed PD location and constant EM signal propagation, the linear correlation between the PD charge and the possible signal sources can be obtained [84], [85]. The EM method was first introduced by W. R. Rutgers for the power transformer in 1997 [86]. Antennas such as conical, spiral, and Vivaldi are used as sensors for ultra-high frequency (UHF) detection [26], [87]. UHF sensors are actively researched due to their advantages such as resistance to low-frequency signals, the negligible effect of noise due to internal transformer construction by implementing denoising techniques and removing white noise, and corona-free pulse disturbance [33], [88]. UHF detection is affected by radio interference and switching events. The hindrance can be eliminated by careful denoising techniques, which are illustrated in section V. The major challenge for the implementation of UHF sensors is the calibration process since the measured amplitude is dependent on a variety of elements.

In [89], the authors examined the effect of different PD types on UHF calibration in a power transformer whose circuit diagram is shown in Fig. 5. PD sources examined are in the form of corona discharge, internal discharge, surface discharge on polyethylene, surface discharge on pressboard, and void discharge. Six drain valves help to install different UHF probes at different locations. The authors in [89] introduced the best possible detection frequency range to measure the UHF signal concerning PD apparent charge. Also, they illustrated the big challenge to reduce calibration error due to active transformer parts thereby, it was inefficient to use the UHF probe. However, the maximum charge estimation method was proposed where the least feasible ratio between the UHF quantifier parameter and IEC apparent charge is achieved in the measurement performed in the laboratory [89].

Different types of current transformers like Rogowski coil, high-frequency current transformer (HFCT), and radiofrequency current transformer (RFCT) have been extensively explored as sensors for the PD detection in power transformer [90]–[92]. The EM method can be used for localizing multiple PDs and identifying individual PD sources through feature extraction and de-noising techniques.

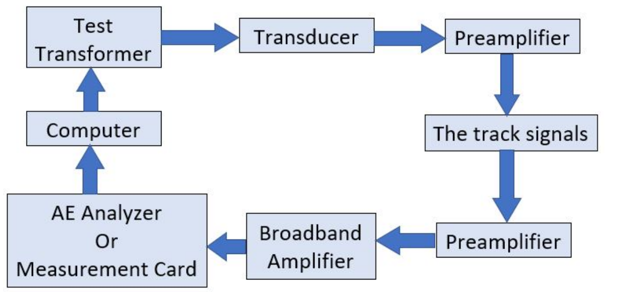

FIGURE 6. **Power transformer recording system for the detection of AE signals from PD.**

C. ACOUSTIC EMISSION (AE) METHOD

AE in the power transformer can be produced by a mechanical explosion due to the vaporization of oil near the vicinity of the streamer, electrical arc, and mechanical vibration [93]. The signals are in the form of pressure waves with unique characteristics for the distinct AE source and can be used to localize the AE source by the detection of ultrasonic signals with a frequency ranging from 40 kHz to hundreds of kHz [94] [95]. However, the acoustic PD signals can be affected by the high-frequency signals which can be removed by denoising techniques. The advantages of having no EM interference and at the same time having an economically friendly technique, have driven the AE method as the most applicable technique for power transformers. Fig. 6 represents the block diagram of the power transformer recording system for the detection of AE signals from PD, which is implemented during the normal operation of the power transformer [96]. Broadband piezoelectric transducers are common transduction elements for many ultrasonic systems. These are fixed on the transformer tank through a magnetic holder for detecting AE signals. The AE signals further undergo amplification, filtration process and are finally fed and recorded by the AE analyzer.

The AE method can be used for detecting multiple PD sources [94]. To overcome the incapability of detection of PD level and calibration, the AE method is combined with other methods such as UHF, optical detection, and electrical detection. The drawbacks of this method are the complex behavior of acoustic emission, low intensity detected signals, and high price. AE detection devices include microphones [97], piezoelectric transducers [94], accelerometer, fiber optic (FO) sensor [98] [94]. Among these AE detection devices, Fiber Optic sensors provide superior results due to wide acoustic field detection and improved signal-to-noise ratio (SNR). By denoising and optimization techniques, noise due to internal transformer design can be eliminated, and multi-PD sources can also be detected. However, the

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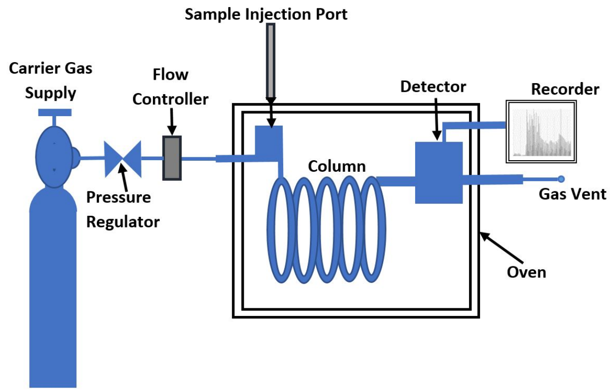

FIGURE 7. A typical gas chromatograph [108]

main problem of the AE technique is the helplessness of PD source localization in the transformer winding due to rapid signal attenuation by passing through different mediums [99].

D. GAS PRESENCE METHOD

Dissolve gas analysis utilizes the concept of detection of gas es released due to the degradation of the transformer oil and cellulose insulation [100]. Degradation of transformer oil results in the liberation of gases in the form of hydrogen (H_2), methane (CH_4), ethane (C_2H_6), acetylene (C_2H_2), and ethylene (C_2H_4). While cellulose insulation mainly releases gases such as carbon monoxide (CO) and carbon dioxide (CO_2). The DGA is limited to offline testing in the form of gas chromatography [101] and air circulation pump method [102] since this method is time-consuming. The air circulation pump method is a type of hydrogen detection system where hydrogen is detected by the circulation effect of the air pump.

The online testing is developed are mainly in the form of hydrogen detection [103], photoacoustic spectroscopy (PAS) [104], fiber Bragg grating (FBG) sensor [103], oil-immersed sensors [105], and membrane-based technique [106]. A typical gas chromatography system is shown in Fig. 7 [107]-[108]. The injection port vaporizes the oil sample. The formed gases, fed into the column, contain lighter gases in the form of argon, helium, nitrogen, and hydrogen. Each gaseous component is filtered out by the column individually based on the retention time and comes into contact with the heat detectors [108]. The detected PD signals are then recorded and plotted with the data acquisition system creating chromatograms. The identification of the gases is performed based on the concentration of the gas and retention time. Generally, hydrogen gas detection is preferred over other detections due to better accuracy. During overheating and discharges, if the hydrogen gas level rises above the warning value, the internal insulations need to be diagnosed [109]. Several types of research have employed FBG sensors inside the tank with the normal operating temperature (60°C to 90°C) for detecting the hydrogen gas concentration. This shows a promising future due to non-interferences from other gases in addition to the

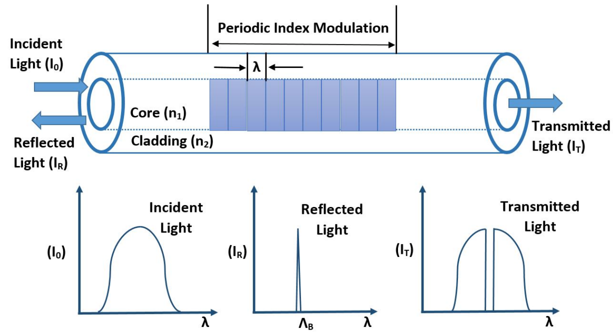

FIGURE 8. Working of Fibre Bragg Grating Sensors [112].

high sensitivity of hydrogen gas detection at 80°C [110]. Also, enhanced FBG sensors (Pd-capped Mg–Ti thin-film-based hydrogen sensor) have been developed which show sensitivity at a broader range of temperature (10°C to 80°C), having considerably higher sensitivity than the conventional FBG [111].

E. OPTICAL METHOD

The optical method can become a support tool for detecting the PD activities in power transformer oil. Researchers have carried out different methods for the PD analysis through the light detection method for transformer oil/paper insulation. Common PD optical detection sensors include Mach–Zehnder interferometry (MZI), Fabry–Perot interferometer (EFPI), and fiber Bragg grating (FBG) [39]. MZI is the early optical fiber-based sensor that uses a single-mode fiber and laser. The beam of light from the source is initially split into two fibers by a fiber coupler. The first sensing fiber optic coil is positioned to the zone of the PD signals in the oil tank and the second fiber is used as the reference for the optical route of the light. EFPI sensor is based on a single optical fiber using a silica diaphragm embedded in the capsuled-shaped silica glass tube. Currently, FBG sensors are used in power transformers as they can be directly kept inside the oil with the additional benefit of having strong dielectric property and immunity from electromagnetic interference.

The working principle of FBG is depicted in Fig. 8 [112]. FBG works as the narrowband reflective optical sensors, where a single wavelength of light is reflected by grating, and the other wavelengths are transmitted.

Initially, in the case of fluorescent optical sensors, PD detection from light emission was found possible for air and not for transformer oil. In 2013, the optical method was found to be reliable for PD measurement in power transformer through the fluorescent sensor with an uncommon technique [113]. However, the research for PD detection in transformer oil through fluorescent sensors led to questionable results with many flaws. The experiments have been continuously carried out to connect photon activity, PD through optical signal, and PD charge constraints in the oil. In 2014, the measurement was possible for power transformer oil [113]. However, this was challenging especially for old transformer oil [114]. The

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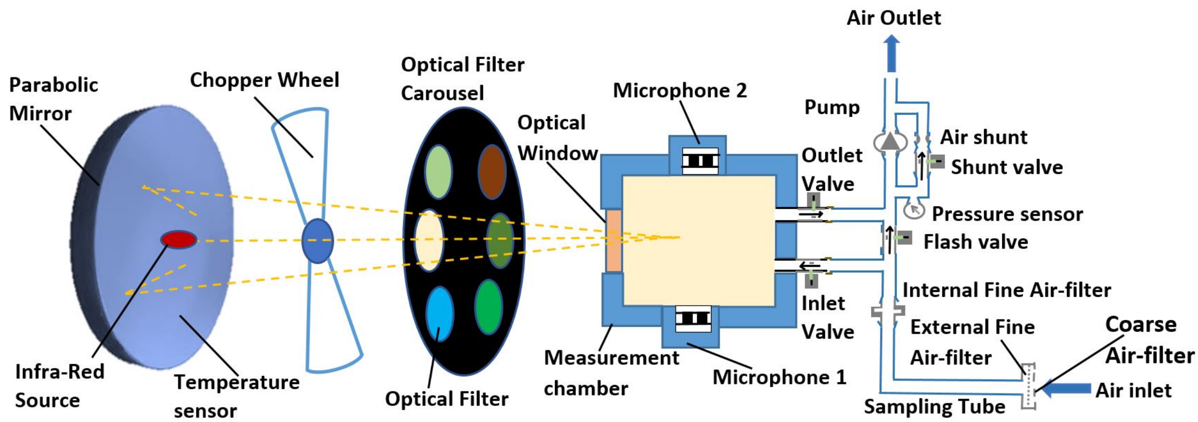

FIGURE 9. Photo-acoustic spectroscopy-based DGA system [117]

advantages of this method are high-frequency response, immunity to electromagnetic interference, measuring a broad range of chemical elements, and physical parameters [115]. However, the major drawbacks are: the detection of PD cannot be calibrated, no information on PD magnitude, and limitation to identify discharges within transparent media. The PD detection and localization in transformer oil are still being researched currently. X-ray emission from PD source is also being researched for detection testing due to the advantage of bypassing the complex geometry of the power transformer.

E. COMBINATIONAL METHOD

For the detection and localization of PD faults in power transformers, the combination of DGA and AE methods has been used. For the existence of PD in transformers, offline DGA has been implemented first, then to locate PD sources, AE detection for 24 hours has been implemented for copying the daily load cycle [116]. Photo-Acoustic Spectroscopy (PAS) is an example of a combination of the DGA and AE method. Fig. 9 illustrates the working principle of PAS [117]. The infrared source provides kinetic energy to the fault gases. Whereas the microphone detects the pressure signal and transfers it into the electrical signals. Different gases detected are based on the intensity of sound waves produced, which are filtered through optical filters. The combination of EM and acoustic methods have been used in which ultrasonic and UHF sensors were arranged in different shapes to provide worthy performance to detect PD sources for a particular distance [118]. An example was proposed with the hybrid PD detecting system by transient earth wire voltage (TEV) and AE sensors [119]. Innovative forms of AE detection methods include AE sensors for locating the PD with a signal from EE for the reference time which allows locating and verifying that the signal detected is not the noise [120].

The combinations of AE, EE, and DGA have been used for the PD identification method to find the overall insulation condition of the transformer [121]. By using EE and EM techniques, a noise rejection system could be created for the PD detection, where data from EE detection can be used to detect the PD source. AE method can be enhanced to have better sensitivity by combining with the EE method where EE detection is used for triggering.

In AE and optical combination method, Fabry-Perot fiber (AE sensor) has been used for PD localization, and fluorescent optical fiber (optical sensor) is used as the confirmation that the reference signal has been initiated from the PD source [122]. Table 1 compares the advantages and drawbacks of different PD detection techniques used in power transformers.

IV. PD DIAGNOSTICS IN POWER TRANSFORMER

PD diagnosis of power transformers is a powerful tool to classify various faults. The main purpose of PD diagnosis is to identify the cause of PD in the insulation and distinguish the type of defects. Since power transformers have a highly complex insulation system with almost inaccessible inner components, PD diagnosis is demanding and challenging. Online testing is performed and limited to the transformer tank and transformer terminals due to the compact structure. For achieving a proper diagnosis, advanced testing devices along with experienced personnel is mandatory.

As per IEC 60270 standards, the PD measurement by the electrical method has excessive noise content due to sensitivity restrictions [123]. The UHF method has a high EM frequency range (300 MHz–3000 MHz) and the PD in transformer oil releases EM waves in the same range. UHF sensors installation can be performed inside the transformer by an oil filling valve during the state of operation, which provides decent PD signal detection due to EM resistance from the surroundings by the transformer tank [124]. To record PD activity by EE or EM method, localization of PD can be performed by the time of arrival of acoustic signals through piezo-electric sensors that are fastened on the wall of the transformer tank [125]. The problem is that the acoustic signals contain distortion due to the complex structure of the transformer. It can be resolved by denoising and crafting averaged signals where acoustic PD signals are overlapped, and the noise is nullified by averaging.

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TABLE I
ADVANTAGES AND DRAWBACK OF DIFFERENT PARTIAL DISCHARGE DETECTION TECHNIQUES IN POWER TRANSFORMER

	Electrical Detection [31]	Chemical Detection [31]	Acoustic Detection [31]	Optical Detection [31], [114], [115],	UHF Detection [33], [35], [124]
Advantages	Convincing recording of PD signals in laboratory. High sensitivity. Low noise level in PD signal. Less signal attenuation.	Convincing recording of PD signals in laboratory. High sensitivity.	Convincing result in real-time. Noise immunity of device for online PD detection. Localization feasible.	Broad variety of chemical and physical parameters can be used. High sensitivity. Immunity for electromagnetic interference. Small size and light weight.	Suitable for online PD detection Improved immunity against external noise High sensitivity and anti-interference Reliable and safe against any induced current
Drawbacks	Tricky to implement online. Fake alarm due to greater sensitivity. Unreliable for long-term condition monitoring. Affected by electromagnetic interference. Susceptible to noise.	No relation of level of dissolved gas with the distinction of type of fault. No relation between the amount of glucose and intensity of dielectric breakdown	Susceptible to environmental noise. Low sensitivity	No detection feasible for solid and liquid insulation. Cannot be calibrated.	Calibration problem Expensive Cannot provide charge quantity of PD

The physical parameters are the main distinction between the EM and EE PD measurement method, where the former measure voltage (in mV) by sensing EM radiation through UHF sensors and the latter measure apparent charge level (in pC) by integrating the recharging current [126]. In factory acceptance tests (FAT), the apparent charge (pC) is acceptable considering the fact that the real PD value (pC/mV) is undetermined s the measurement is not directly taken [127]. UHF sensors can overcome the challenge of online monitoring due to surrounding noise and the occurrence of corona discharges since the UHF antenna can measure PD incidence in transformer oil as the transformer tank behaves as the Faraday cage [85]. By this advantage, UHF sensors can be implemented for offline as well as online routine tests. EE and EM measurements are predominantly affected by the type and the level of PD source, signal diminution in the connecting path, sensitivity of the sensors, and measurement device sensitivity.

The effect of quadrupole or coupling capacitor in the sensitivity of electrical measurement can be amended by the calibration process. For this, the parameter antenna factor (AF) should be identified. AF depends on the design in terms of EM waves and can be estimated by an oil-filled gigahertz-transversal-electro-magnetic setup (GTEM) cell [124]. The construction of the GTEM cell comprises of an elongated coaxial cable in a cell, and with isolation from surrounding EM disturbance, a known EM field is introduced to the equipment under test (EUT). GTEM cell is considered as the initial step of calibration and reflects only the effect of the sensor. For the competency of the measurement, the UHF antenna is connected to the transformer for measuring the calibration sensitivity. In [124], firstly, an identified UHF calibration impulse is introduced without an antenna for calibrating cable and measurement devices. Then, the sensor feature is added to the calibrated path by applying AF. Introducing the identified transfer function through frequency-dependent, AF can provide variation of the calibration point from calibrator to antenna in the transformer. The calibration process can be shortened by using scalar correction factor AFs, showing PD frequencies with enough accuracy. Power transformer online monitoring with diagnostics has become a necessity now due to the majority of transformers being installed more than four decades back [128]. Performing continuous monitoring help to detect and resolve sudden faults which minimize any future hazards. The data generated through monitoring are very high and therefore need further analysis. One of the common analyses is phase-resolved PD pattern analysis based on pattern recognition. The characterization of PD patterns received from online monitoring is performed and compared with the recognized pattern [33].

V. PD DENOISING TECHNIQUES IN POWER TRANSFORMER

Partial discharge pulses are irregular, short-lived, and non-periodic. The obtained partial discharge signals extracted from the PD sensors contain excess discharge impulse, which is challenging for the processing task. The obtained signals need to be disintegrated further by signal processing techniques. Taking multiple PD sources generated at different insulation into consideration, the signal processing techniques becomes handy. The process is conducted by applying the time and frequency characteristics of obtained PD signals to create unique collections of time-frequency maps. Each collection is allocated to a PD source. Various signal denoising techniques are fast Fourier transform, low pass filtering, Wigner-Ville Distribution, short-time Fourier transform, least mean squares (LMS) approach, frequency-domain adaptive filtering (FDAF), recursive least squares (RLS), and exponentially weighted recursive least squares (EWRLS) methods, matched filtering, notch filtering, wavelet denoising, artificial neural network, empirical mode

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decomposition, and blind equalization [129]–[132]. Some common denoising techniques are explained as follows:

A. FAST FOURIER TRANSFORM

FFT is the algorithm developed for computing discrete Fourier Transform (DFT) which is applied to the PD signal to transform from the time domain to the frequency domain [133]. FFT is effective for the slow varying signals having stationary components. Since the property of PD signals is rapidly changing, non-periodic, irregular, and transient in nature, therefore, Wavelet Transform is preferred over this method [134].

B. WAVELET TRANSFORM

Fourier transform decomposes any signal into sinusoidal waveforms along with the frequency domain, but the time data is absent. Wavelet transform is used to decompose the signals and is a small waveform that has a very short period and with zero average magnitudes [135]. These are time-domain signals in the form of two-dimensional sets of coefficients and, therefore, confining them into the time and frequency domain. They are employed for finding parameters such as the breakdown points and noise elimination [136]. The signal is fragmented into different wavelet coefficients into different frequency ranges. The wavelet transform can rebuild the PD signals when the wavelet function counterparts the PD signals. By the thresholding, the wavelet coefficient of PD signals is retained and the rest are eliminated [132].

The two different ways to prepare the wavelet transform are continuous wavelet transform and discrete wavelet transform [137]. The former acquires the surface of wavelet coefficients, while the latter has the discretized scale and translation.

C. ENSEMBLE EMPIRICAL MODE DECOMPOSITION

Ensemble empirical mode decomposition (EEMD) is a method which is used to extract Intrinsic Mode Function (IMF) from the signals and can be handy for non-stationary and non-linear signal [131]. Hilbert Huang transform (HHT) comprises two sections: Ensemble mode decomposition (EMD) and Hilbert spectral analysis. HHT is widely used in fault analysis but contains flaws in the EMD technique, where the problem arises due to the mode mixing problem during the sifting process. EEMD is a noise-assisted analysis technique that is more robust with better accuracy [138], [139]. PD signal is disintegrated by eliminating the riding waves and smooth irregular amplitude that could be rooted in the IMF. This is termed as a sifting process that limits the upper and lower measured signal, evaluates the average values of the boundaries, and deducts them from the measured signal. In general, IMF is a single component signal, but the IMF repeatedly clinches disparate frequency signals. This procedure is further reiterated on the residual part of the measured signal until all the IMF is acquired. The signal can be rebuilt by adding all IMF. For improving the discrimination of noise and PD signal in EEMD, synthesized white noise is added to the measured signal as sometimes they fail to distinguish them [140].

In [139], the self-adaptive denoising techniques by using EEMD were proposed to eliminate the drawback of WT and EMD. By utilizing the kurtosis-based selection criterion, the EEMD method was found to be effective in reducing the noise to a great extent and retrieve PD impulses without conceding the quality of PD impulses.

D. MATHEMATICAL MORPHOLOGY

This technique necessitates earlier knowledge of the repetitive frequency of the signal, which cannot be availed in some applications. The theory of mathematical morphology is centered on a mathematical operator that is implemented between the measured signal, and the structured element (flat, sinusoidal, or triangular element) [141]. The filtration of the PD signal is done by the overlapping of the structured element and the measured signal, where the filtered signal is denoted as a morphological feature [40]. In [139], the mathematical morphology was found to be noteworthy for denoising the PD signals.

E. BLIND EQUALIZATION (BE)

Blind equalization is the type of de-noising technique where higher frequencies are eliminated, which are generally produced by communication systems and radio transmission at substations [132]. Blind source separation (BSS) and BE are targeted to retrieve source signal without evaluating the source [142]. Also, there is a drawback that it requires more numbers of PD sensors than that of the number of PD sources.

In [132], the author proposed an automatic BE technique for denoising PD signals in power transformers where techniques BSS and BE were used for recovering the source signal without evaluating the source. The denoised PD signal validated the effectiveness of the PD extraction by suppressing the high noise level.

F. ARTIFICIAL NEURAL NETWORK

The multilayer feed-forward neural network (MLPFNN) has become the center of attention to denoise the PD discharge signals [130]. Function approximation is applied due to the capability to discover the bond between the input and output data with the weights of these connected input and output data that are updated by the backpropagation algorithm. The Lavenberg-Marquardt algorithm that is used to manufacture perfectly denoised PD signals by changing the number of nodes in the hidden layer is implemented in the hidden layers for enhancing the performance of MLPFNN [143]. To improve the quality of the denoised signal, the number of nodes in the ANN architecture is increased keeping in mind the processing time.

Some research works have been performed to investigate the capability of ANN-based PD signal denoising techniques [130], [144]. In [130], the authors implemented the comparison of the performance of ANN with fast Fourier transform (FFT) and wavelet transform (WT) to conclude the ANN-based denoising technique to be superior to other

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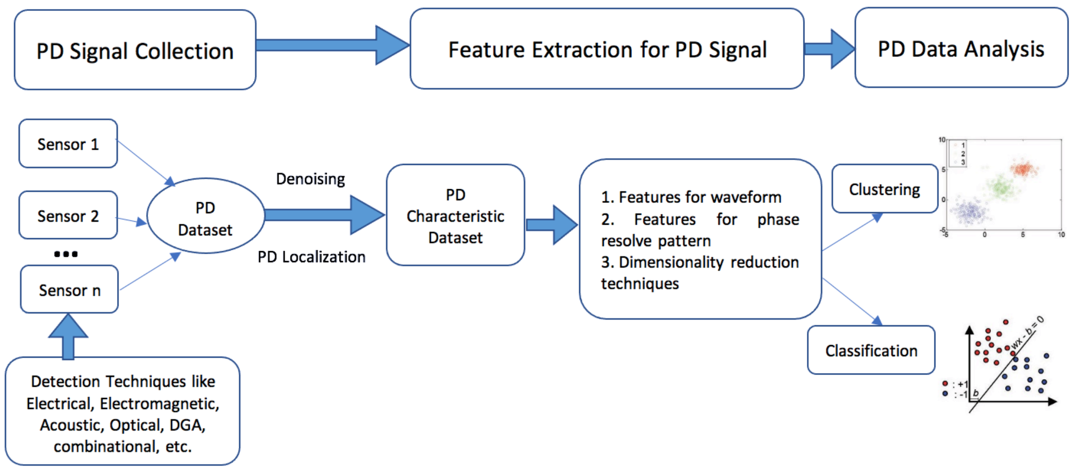

FIGURE 10. Flowchart for partial discharge monitoring system.

techniques. In [144], the authors performed ANN (curve fitting and function approximation) and WT (energy conservation-based method (ECBT)) denoising technique to remove white noise of radio frequency (RF) signals for ceramic disc insulators having defects in the form of internal voids, cracks, and sharp points. The result of ANN-based denoising was found to be better than ECBT.

VI. FEATURE EXTRACTION OF POWER TRANSFORMER

Feature extraction is an important process for the analysis of the PD signals of the power transformer. Common feature extraction techniques include Fourier transform, wavelet packet decomposition, Hilbert–Huang transforms (HHT), stochastic neighbor embedding (SNE), principle component analysis (PCA), kernel principal component analysis (KPCA), support vector machine (FSVM), and artificial neural networks (ANNs) [145], [51]. This section is focused on the statistical overview of feature extraction in power transformers. Fig. 10 represents the flowchart of the partial discharge monitoring system. The monitoring system comprises of three sections, namely PD signal collection, feature extraction for PD signal, and PD data analysis. After applying the denoising techniques and localization of PD signals, the filtered data can be represented by two different patterns, namely PRPD and TRPD. While analyzing PD, very high dimensional data are quite common, which require dimension reduction techniques. PRPD characterization can be classified into two different groups; the number of PD pulse vs. phase angle and amplitude of charge vs. phase angle which can be categorized further in positive and negative half-cycles [146]. Statistical features that can be obtained from these distributions are namely skewness, mean, variance, kurtosis, and Weibull [147]. The advantage of statistical features is decreased computation time. In [148], the author included a statistical feature analysis for the extraction of PD signals in transformer insulation defects. Kurtosis and skewness show the sharpness and symmetry of the distribution respectively. Weibull distribution portrays the pulse height analysis pattern where the PD pulse rate can be shown in the probability distribution curve. The features of Weibull distribution in addition to other parameters after analysis are served to the intelligent classifiers.

Fractal features can be applied to model PD and pattern recognition due to the ability to model complicated structures and natural phenomena where presently, the mathematical means are inadequate [149]. In [150], the author performed fractal-based feature extraction for the identification of PD patterns for high voltage power transformers. PRPD patterns can be processed through box-counting techniques that use two fractal features; fractal dimension (computation for image surface) and lacunarity (fractal surface compactness) [150]. Even though fractal dimension does not affect due to variation in scale and promising measurement of the surface coarseness, the ineffectiveness to distinguish feature of the same value of fractal surface resulted in the development of another variable termed lacunarity [151]. The research was performed based on the removal data contaminated by noise in which PRPD patterns were transformed into a binary image, and fractal features calculations were performed through ImageJ [146]. Principle component analysis (PCA) is used to filter essential data from big data groups thereby serves as the data reduction techniques [152]. PCA, also termed as Karhunen-Loève (K-L) method does not negotiate with the data information, and with very low depletion of information, data can be shrunken to compact space. Space reduction is attained through data projection in the broadest variance at the lesser dimension that will boost the scatter of the desired samples [153]. The number of principal components for attaining the precise value of actual data can be achieved through a scree plot, which is the graph of eigenvalue magnitude vs. its number [148]. In [92], PCA was implemented for the autonomous localization of the PD source within transformer winding showing the capability to locate the PD source.

Machine learning techniques (Artificial neural networks) have currently shown decent efficiency for PD

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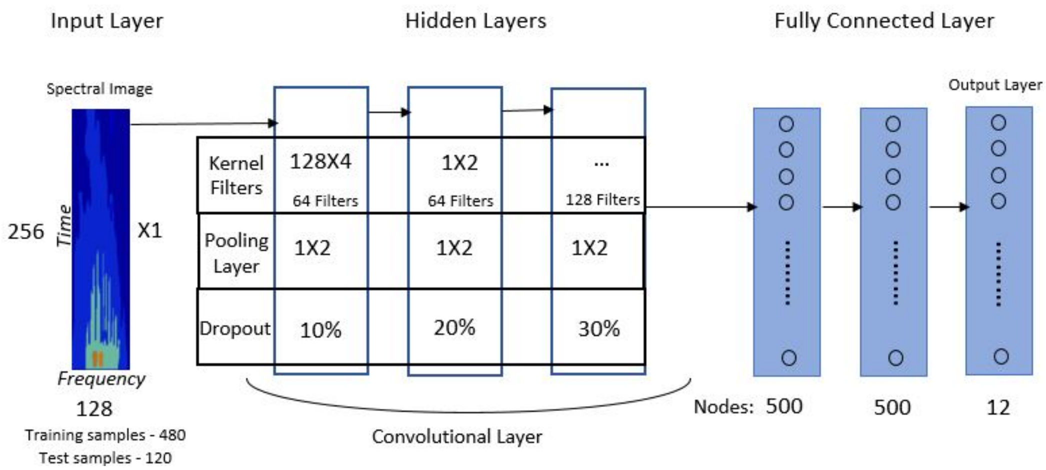

FIGURE 11. **Convolutional Neural Network- based PD classification** [161].

detection and recognition [154]–[156]. In [157], the authors used four types of artificial PD defects (floating, surface, rod-plane, and air gap discharge) for PD identification, which is similar to the intelligent framework for power transformer assessment as proposed in [158]. A deep learning approach called sparse auto-encoder (SAE) was used for feature extraction. The deep learning method of SAE and Softmax exhibited promising results of more than 96% accuracy.

VII. PD CLASSIFICATION IN POWER TRANSFORMER

PD classification in the transformer is a valuable supervised learning technique since it can organize various kinds of defects into their respective category for condition assessment. These appropriate classifiers are necessary as any indecision may result in the wrong classification of the PD model. Also, the precision of the PD classification depends on the features extracted through the PD pattern. Recent artificial intelligence techniques have shown decent PD classification of PD defects in power transformers.

ANN can be the proper classification for PD pattern analysis due to the insensitivity to the minor input deviation and making appropriate decisions during the training process while feeding the data that is quite similar to the input data [159]. ANN is the supervised learning process where training employs forward and backward processes, and initialization is performed through the weights and biases having small value [160]. The activation function provides the computation of the feature vector in their respective output layers. The layers in between the input and output layers that are connected and cascaded together to form a network are termed hidden layers. Hidden layers attribute to acquire the PD features from various sources and send the extracted sources to the output. The classification is done based on the types of PD defects to be classified. In [161], the author proposed a convolutional Neural network (CNN) architecture for UHF signal PD pattern source recognition which is shown in Fig. 11. The input to CNN is lx128x256 generated by Short Time Fourier Transform (STFT). The first three hidden layers comprise filters, pooling layers, and dropout layers. The final two hidden layers are fully connected with 500 hidden units each, and the output layer is a fully connected linear layer. By the proposed architecture, the data accumulated from gas-insulated switchgear showed decent accuracy and further help in developing more ideas for PD UHF signal recognition for power transformers.

Adaptive Neuro-Fuzzy Inference System (ANFIS) is the hybrid system of neural network and fuzzy system that uses a neural network to eliminate the necessity of finding a suitable fuzzy network for operation [162]. Takagi and coworkers created ANFIS that is based on the fuzzy Sugeno model, which is a proficient tool for classifying PD patterns by implementing If-Then rules through a decision tree andspecified input-output data [163]. For improving the efficiency of the training, input variables are regularized between zero and one. In [164], the authors implemented a fuzzy and ANFIS model for PD fault detection using DGA for power transformer where the ANFIS model was found to be superior with an accuracy of 98%.

Support vector machine (SVM) is derived from statistical learning, where the regulation is managed for several tasks by applying base algorithms and kernel functions [165]. In this method, PD pattern data can be portrayed by vector dimension depending on the number of input features and perform decently in the complications related to non-linearity, lesser sample magnitude, and large dimensions [166]. Kernel's method is the additional tool to overcome the inefficiency to analyze non-linear problems.

The authors in [167], performed the classification of PD pattern based on SVM for the floating metallic particles in the transformer oil showing promising results irrespective of big data and complexity. In [168], the authors performed different PD classifications for the AE-based signals for transformer insulation where SVM performance was found to be superior to the decision tree and K-nearest neighbor.

The decision tree method comprises a type of flowchart assembly in which the internal node is used for the feature

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TABLE II
RECENT TIMELINE OF PARTIAL DISCHARGE ANALYSIS IN POWER TRANSFORMER

Reference, Year	PD Defects	Technique	Feature Extraction	Classification/ Clustering	Conclusion
[30], 2000	Calibrated PD source (0, 100, 1000 pC) in transformer bushing	Offline electrical PD detection using a spectrum analyzer and Phase resolving PD analyzer	PRPD signal		Detection of several critical PD defects and achievement of better sensitivity than 50 pC
[49], 2006	Two hypodermic needles of 0.1 mm diameter separated at 0.5 mm in the tub of transformer oil	Fiber optic sensor and piezoelectric sensor (acoustic frequency response of 5 MHz) used in the wall of the sample tank			Detection of PD signals with the surrounding noise and localizing the PD signal
[169], 2011	Conducting particles of different sizes introduced deliberately into the transformer oil	Circuit designed for both electrical and acoustical measurements of PD	Particle Swarm Optimization based approach	Support vector machine classifier (SVM)	Can be effectively used for online PD recognition measurements.
[29], 2012	Internal and surface discharge for oil-paper insulation	Electro-acoustic Detection	PRPD signal and Statistical analysis		Recognized different PD sources employing energy ratio. Able to locate PD source by cross-correlation and statistical analysis
[170], 2012		Three UHF probes installed in three oil valves each and piezo-electric sensors at the outer tank	Statistical analysis		This method is effective in using low-frequency electric or UHF signal for triggering PD signal and using the acoustic signal for denoising
[171], 2012	Corona discharge, Surface discharge, Gas cavity discharge, and floating discharge in oil	UHF Hilbert fractal antenna for online PD detection			Can be effectively applied for online UHF PD monitoring of transformers and can be used for PDs recognition.
[42], 2012	PD fault based on the inspection of dissolved gas analysis	Acoustic emission approach using the modified binary partial swarm optimization (PSO) algorithm	Wavelet transform and denoising	modified binary PSO algorithm	Capable of localizing and detecting two PD sources with minor errors compared to the Genetic Algorithm method.
[82], 2014	Floating metal particle between HV windings and LV windings	UHF detection			PDs near 500 pC inside the transformer windings could be located and detected.
[172], 2014	Void, floating metal and their combination	UHF detection and recorded by spectrum analyzer and oscilloscope	db2 and sym2 wavelets and denoising	feed-forward neural network	Classification and recognition of single and multiple PD phenomena with good accuracy
[173], 2014	surface discharge in oil-paper insulation	Constant voltage testing on the model in the laboratory	3-D spectrum of φ-W-n, wavelet moment	Euclidean distance clustering	This clustering method shows the “hold together” characteristic for wavelet moment
[96], 2014	Surface, bubble, and corona discharges in oil	Acoustic Emission Method	Short-Time Fourier, and Wavelet Transform	one-direction multi-layer neural network	Implementation of an effective but expensive computer-based expert to analyze the transformer technical condition
[174], 2014	Corona, surface, and internal discharges	Combination of Acoustic emissions with several piezoelectric (PZT) and fiber optic sensors.	Denoising	Look Up Table based 3-D location algorithms	detection and location of AEs generated by PDs with an accuracy of 1 cm.
[34], 2014	Contaminated oil in a test tank in laboratory	Three Radio-frequency coils attached to the transformer tank for PD detection			Provides, reliable early-stage detection for online PD detection.
[175], 2015	Sharp point to the ground, surface discharge, void in the insulation, and semi-parallel planes	Acoustic Emission Method	Discrete Fourier transform, wavelet decomposition, and principle component analysis (PCA)	K-nearest neighbor, polynomial classifier, quadratic discriminant analysis, SVM	Effective when PCA is used as the feature extractor with KNN as a classifier. High-frequency AE sensors of the range of 100- 450 kHz provided good detection for different PD sources.
[176], 2015	Artificial PD defect/source	UHF detection in the valves of tank model and real power transformer by installing several new UHF antennae			Enhanced accuracy of PD localization by increasing the distinction between potential PD locations inside the transformer

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TABLE II (Continued)
RECENT TIMELINE OF PARTIAL DISCHARGE ANALYSIS IN POWER TRANSFORMER

Reference, Year	PD Defects	Technique	Feature Extraction	Classification/ Clustering	Conclusion
[112], 2015	The emulated PD generation system	Fiber Bragg Grating (FBG) based optical PD sensor which detects acoustic pressure generated during PD			Can be used for online monitoring. Can be placed inside the transformer tank. Better than the conventional method
[177], 2015	Cavity discharge in pressboard, surface, and corona discharge in oil, and discharge in oil/air interface	Two-dimensional linear discriminant analysis (2DLDA)	Two-directional modified fuzzy-weighted 2DLDA (TD-MFW-2DLDA)	Fuzzy C-means clustering and SVM with genetic algorithm	TD-MFW-2DLDA removes the multi-factor effect of the defect size, applied voltage, and insulation aging on the PD pattern recognition
[135], 2015	Internal discharge, corona, surface discharge, discharge in oil, and discharge due to floating particles	An inductive system using a high-frequency current transducer (HFCT) installed on the transformer's grounding wire	Mother wavelet selection, decomposition level determination, and thresholding	Binary decision	The proposed method is better than the conventional single threshold-based wavelet transform.
[178], 2016	Point to Sphere discharge, Surface Discharge, and Floating Potential discharge	Combination of UHF and Acoustic PD detection Techniques		--	Ability to recognize the unique signals unique to the individual PD source.
[179], 2016	scratch on winding insulation, bubble in oil, moisture in insulation paper, very small free metal particle in transformer tank and fixed sharp metal point on transformer tank	Test circuit for PD measurement	Statistical and Texture feature	SVM	Texture features show the highest accuracy when the different types of defects are classified.
[89], 2017	Corona discharge, internal discharge, surface discharge, and void discharge	UHF PD detection system using UHF probes at six different drain valves in transformer tank model		--	The very high error indicates that PD calibration using UHF probes is not feasible. But, the maximum-charge estimation method can be implemented.
[45], 2017	Artificial PD defect/source	Acoustic emission method to locate and estimate the propagation time of acoustic waves by Particle-Swarm-Optimization-Route-Searching Algorithm		--	Localization detections when compared with different methods show better detection accuracy
[180], 2017	point-plane electrode	Acoustic emission-based localization to estimate the time of arrival by the source-filter model of acoustic theory	source-filter model	--	Localization accuracy of about 1 cm.
[94], 2018		Sagnac fiber sensor system designed to determine the advantage of using fiber optic sensor for PD acoustic detection.		--	Outperformed piezoelectric transducer to detect AE signals originated inside the winding
[181], 2018	Needle-plane model	The complete internal structure of a three-phase oil-filled transformer was used to study the propagation characteristics of EM waves			The EM signal's amplitude decrease nonlinearly, and with increasing distance from the PD source, the attenuation rate slows down
[44] 2018	Needle-plane electrode	AE method to determine the characteristic of transformer oil for a temperature range of 30–75 °C.	fast Fourier transform (FFT)		The amplitude of the AE signal reduced from 65 °C to75 °C at 17 kV due to change in parameters like viscosity and BDV
[182], 2018	needle-plate electrode	AE method consisting of Fabry-Pérot optical fiber sensor array with Steered Response power sound-source localization algorithm			Better accuracy than the traditional piezoelectric transducer

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TABLE II (Continued)
Recent Timeline of Partial Discharge Analysis in Power Transformer

Reference, Year	PD Defects	Technique	Feature Extraction	Classification/ Clustering	Conclusion
[50], 2019	Artificial PD defect/source	A Combinational method: AE sensor is placed inside the end part of the UHF probe.		--	The integrated sensor exhibits higher sensitivity than with direct acoustic wave detection
[183], 2019	Water Content of Transformer Insulation Paper	Optical detection using optical fiber sensors		--	Correlates nicely with a water activity probe effective in different dielectric oils.
[184], 2019	Void, surface, and floating electrode		Discrimination algorithm	density-based spatial clustering of application with noise fuzzy maximum likelihood	The multi-step discrimination method can distinguish and separate mixed signals with similar shapes which were not feasible by the one-step method, or improve the separation capability in sub-classes, which is a better selection than three or more PD sources

testing, the leaf node shows the class label, and the route between the root and the leaf shows the classification rule [185]. This method has been used extensively in the PD classifications under different PD conditions due to the advantage of the visible rule for PD classification, unlike SVM or ANN. A decision tree had been employed to identify the void size and differentiating the multiple PD sources in power transformers [186]. K-nearest neighbor (KNN) is a simple and non-parametric algorithm that classifies the training sets by recognizing the collection of k objects nearest to test objects and allotting the type through correlation of the respective class in the neighborhood [187]. The main elements of KNN are labeled objects, constant 'k', and the quantity of nearest neighbors. The classification of KNN is centered on fresh data points according to greater votes for the neighboring data points.

VIII. PD CLUSTERING IN POWER TRANSFORMER

PD signal clustering is the unsupervised learning technique where the data are organized into clusters such that each cluster element is closely associated with the other. The clustering technique is extensively used in PRPD and TRPD for distinguishing the characteristics of PD pulse in the multiple PD sources and arranging in groups. Table II shows a recent timeline of partial discharge analysis in power transformers.

K-means (KM) is an efficient and uncomplicated centroid-based clustering algorithm where parameter 'K' represents the pre-defined number of clusters chosen for iteration. K-means clustering is applied until the convergence between the assignment step, and the update step is achieved [188]. However, this method has limitations in the form of local minimum convergence and pre-assigned value of K, which may be challenging due to the lack of information regarding the numbers of different PD sources [189]. Another version of K-means is Fuzzy C-means (FCM) in which in each cluster every object is assigned a fuzzy degree [190], [191]. Soft clustering is done for each object where each object can be allocated in different clusters while optimizing. In [192], the author proposed K-means with SVM clustering-based techniques for DGA in the power transformer for improving accuracy. The result found was better for KMSVM relative to SVM and k-mean clustering with a reduction in the training set and training time.

The density-based spatial clustering of applications with noise (DBSCAN) is the clustering algorithm prepared by Martin Ester and coworkers in 1996 [193]. Unlike K-means, DBSCAN does not require allocation of the number of clusters but assigns the data which are dense and closely related in clusters. However, DBSCAN fails in the proper clustering of similar density data and high dimensionality data. DBSCAN works on the two parameters: the number of minimum points in the neighborhood of point p (Minpts), and the radius of neighborhood p (Eps). In [194], the authors performed automatic pulse grouping through DBSCAN for PD source separation in power transformer where the effectiveness of the DBSCAN algorithm over conventional means is evident. The PD sources are notable by the DBSCAN algorithm, whereas conventional cannot completely separate the PD sources. Furthermore, by the PRPD diagram, the different sources are noticeably recognized.

Hierarchical cluster analysis is the clustering algorithm where the clusters are generated in the order of dominancy from top to bottom (divisive) or bottom to the top way (agglomerative) [152]. In the agglomerative hierarchical clustering, objects are initially taken as separate clusters. Further, according to the distance between the two objects, the individual clusters are merged, and the procedure is followed until the conditions are fulfilled. Divisive clustering has initial single clusters where all objects are allocated and further separated into different clusters according to the condition [195]. This method can be productive for examining big structures but slow in processing. Also, it lags modification after developing the splitting/merging decision.

IX. CONCLUSION

This paper enumerates the comprehensive survey of modern techniques for PD signal analysis of power transformers. PD detection, localization, and severity of fault can be analyzed through feature representation, classification, and clustering

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techniques, which are extensively reviewed. Different methodologies for denoising the PD signals have been introduced. PD detection in the power transformer is essential since the power system network depends completely on continuous operation. The paper explains the overview of partial discharge with different types of defects in power transformers. Different types of PD detection techniques (electrical and non-electrical) have been explained, and the advantages and disadvantages of each technique have been elaborated. The importance of PD diagnostics for identifying the type of power transformer PD defects has been elucidated. The PD monitoring system consists of different steps for analyzing PD defects. This includes PD detection, denoising, feature extraction, classification, and clustering. Each step has been elaborated, including the insight of the modern methods. The online PD measurements in a power transformer are proficient means for PD analysis with the challenge of the onsite noise and due to the complex structure of the power transformer. PD sensing techniques can be advanced to reduce the impact of white noise in online sensing and to locate PD activities in the power transformer.

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