

Received August 27, 2021, accepted September 14, 2021, date of publication September 24, 2021, date of current version October 5, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3115519

Partial Discharges Classification Methods in XLPE Cable: A Review

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This work was supported in part by Universiti Sains Malaysia (USM) under the Research Universiti Grant (RUI) 1001/PELECT/8014050 (UO1620/2018/0320), and in part by the Ministry of Higher Education, Malaysia, under the Fundamental Research Grant Scheme FRGS/1/2019/TK04/UNIMAP/03/8.

ABSTRACT Partial discharge (PD) signal classification analysis on cross-linked polyethylene (XLPE) cables is complex, requiring a comprehensive understanding of the characteristics of PD patterns. In the realm of high-voltage electrical insulation, PD pattern characteristics, such as PD charge and inception voltage, are essential as assessment criteria in diagnostics systems using PD classifiers. This paper provides a review of the various PD patterns and classifiers used by previous researchers, specifically for XLPE cables. In addition, the differences of the studies on various sensor developments based on PD detection in the past 27 years are also discussed. The repeatability, recognition accuracy, recognition speed, and effect of feature sizes on each PD classification method are reviewed and explained. This review indicates that the pattern recognition for PD signal using artificial neural network (ANN) exhibits better performance than the other methods in terms of accuracy and repeatability, and the reduction of feature size does not affect the accuracy of ANN.

INDEX TERMS Partial discharge (PD), cross-linked polyethylene (XLPE) cable, solid insulator, pattern recognition, feature extraction, artificial neural network (ANN).

I. INTRODUCTION

Power cables are an important part of power systems that have transmission lines of different voltage grades and distribution networks of over 100 years [1]. Power cables are widely used in medium-voltage (MV) and high-voltage (HV) power system networks. Approximately 80% of the 33-, 22- and 11-kV networks are underground cables with approximately 180,000 km of MV cables in service [2]. Cable failures have become one of the greatest problems of the power industry. The insulation failure of power cables could impact many customers due to unexpected power outages. In Malaysia, cross-linked polyethylene (XLPE) cables are widely installed through the existing network of cable lines due to their excellent electrical, thermal, and mechanical properties [3]. Among its numerous advantages, the XLPE cable has a lightweight structure, excellent electrical

properties, a heat obstruction feature, and a high transmission limit and is simple to introduce and easy to twist [3], [4]. In Peninsular Malaysia, MV cable failures have contributed to 53% of the power system breakdown, as shown in Fig. 1. The data indicates that 72% of the failures are attributed to the cable joint, whilst 22% and 6% are from the cable insulation and the termination, respectively [2]. According to Halim *et al.*, most of the reliability issues originate from MV underground cable joint failures contributing to 60% of the annualised System Average Interruption Duration Index of Tenaga Nasional Berhad (TNB), Malaysia for many years [5]. When discussing the reliability issues of joint cable failures, the concern is the unscheduled interruption that causes faulty electrical equipment. According to the TNB statistics [6] in Fig. 2, the highest percentage of unscheduled interruption was experienced in 2013, i.e. 9.92%, which is slightly higher than the 9.45% recorded for the previous year per 1000 customers. The lowest percentage of unscheduled interruption was recorded at 6.68% in 2016. This interruption

The associate editor coordinating the review of this manuscript and approving it for publication was Zahid Akhtar¹.

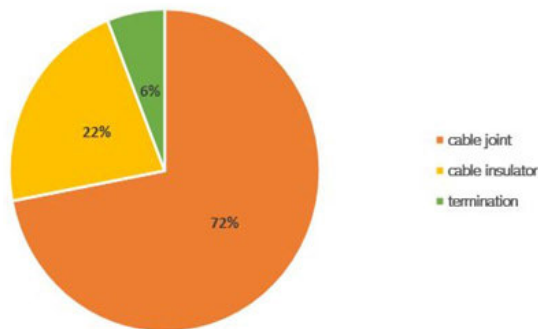


FIGURE 1. Failure of power cable in Malaysia [2].

Performance of Distribution System in Peninsular Malaysia, 2012 – 2018

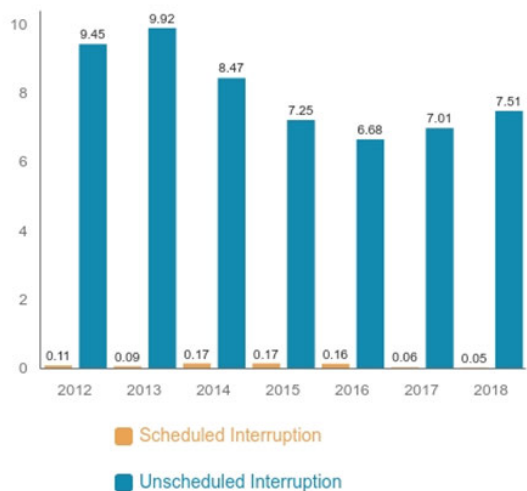


FIGURE 2. Performance of distribution system in Peninsular Malaysia, 2012–2018 [6].

trend shows that the fundamental issue of cable joint reliability and the subsequent choice of cable joint technology remain unresolved [5]. Since 1998, TNB has investigated the partial discharge (PD) activities on XLPE, paper-insulated lead-covered (PILC), and the combination of XLPE/PILC cables with 209 feeders that are more than 10 years old [2]. The test requirements in compliance with international standards require the PD magnitude to be less than 10 pC in the factory [2] and the cables to be longer than 2 km [7]. Nevertheless, for the cable system performance to have good sensitivity, the PD magnitude must be less than 1 pC [7].

Table 1 shows the PD results obtained from the three types of cable six months after installation [2].

The test result reveals that the 11-kV-rated PILC cable contributes 98% PD with an average PD magnitude discharge that is three times higher than that of XLPE cables [2]. However, the experiment did not mention the type of PD in the cables, resulting in difficulty in identifying the causes of PD. Therefore, the PD types must be monitored and classified to identify the root cause of PD activities and estimate their harmfulness. A rehabilitation approach is required to differentiate between the PD from vital sources and other noise

TABLE 1. Results of PD measurement based on types of cable [2].

Type of Cable	Voltage Rating	Feeders with PD	Average Value of PD
XLPE	11kV	8%	5,949pC
	22kV	57%	3,648pC
PILC	11kV	98%	15,589pC
	22kV	61%	1,980pC
Combination of XLPE and PILC	11kV	100%	23,362pC

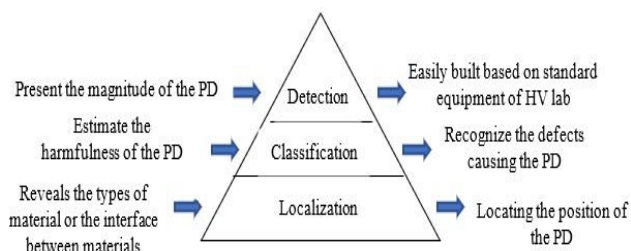


FIGURE 3. Three stages to evaluate PD phenomena.

to avoid losing a PD source before failure or accidentally shutting down a PD-free cable system.

PD is an important cause of insulation degradation and electrical equipment breakdown, contributing to the risk of damaging a power grid’s safety without any continual prevention [8]. PD also causes electrical aging which can be a symptom of thermal, mechanical, and environmental aging in a HV apparatus of over 70 years [8]. According to IEEE 400.3-2006 [9], PDs are small electric sparks or discharges that occur in defects in insulation, at interfaces or surfaces or between a conductor and a floating metal component (not connected electrically to the HV conductor nor the ground conductor). PD also occurs between floating metal components if the electric field is high enough to cause the ionisation of the gaseous medium where the components are located [9]. According to IEC60270 [10], PD is an electrically localised discharge that partially bridges the insulation between two conductors. Meanwhile, researchers [11] reported that continuous PDs degrade the insulation material, inevitably leading to insulation breakdown. All these definitions mention PD as the main indicator for assessing the integrity of power cable insulation and the cause of insulation degradation [12].

Discharge events can be influenced by different factors, such as the type of applied voltage, the insulation material, the conductor material, configuration, humidity and pressure [13]. Three stages of PD evaluation must be considered, namely, detection, classification, and localisation, as portrayed in Fig. 3.

Since the 20th century, many researchers worldwide have shown interest in PD recognition, conducting studies on PD source classification. In line with the advancement of digital electronics and signal processing techniques, various artificial intelligence (AI) techniques, such as artificial neural networks (ANNs), genetic algorithms, knowledge-based system, fractal models, wavelet transformation, and support

vector machines (SVMs), have been used to classify PD sources [14]. The solution to overcome PD issues is difficult to determine without classifying the defects that are causing PD. Each defect has its symptom and effects on power cable performance. However, the data related to how frequently PD source classification in power cables has been performed is limited.

In this study, a comprehensive review was carried out to discover and suggest the most accurate method with the highest repeatability, shortest processing time, and minimum data size requirement for all pattern recognition and data classification methods for PD faults in XLPE cables. The review includes the recognition of PD activities using statistical analysis methods and AI application in the classification system. The best methods for identifying and classifying PD must have the highest accuracy and data repeatability and the shortest processing time.

II. TYPES OF PD IN XLPE CABLE

According to Gao *et al.* [15], the insulation failure of power cables could occur because of several factors: equipment performance, such as cable defects during manufacturing, insulation deterioration and malfunctions; human effects, such as potential human error, quality of workmanship, installation and handling; abnormal system conditions, such as overcurrent and overvoltage from system maloperation and lightning; damages caused by road digging and thermal, mechanical, and earth movements. In addition, Rohani *et al.* recently stated that insulation degradation occurs due to the aging process, environmental factors, mechanical damages, operational stress and manufacturing defects [16]. During manufacturing processes, various defects, such as voids and contamination inside power cables, may appear and be the main source of PD under high electric field (EF) activity, as mentioned in [17]. These studies indicate that power cables are easily affected by surrounding factors and not only by the cable itself or its termination. The PD phenomena in MV cables can be categorised as corona discharge, surface discharge, internal discharge, and discharge by electrical treeing [18]–[20], depending on their location. The fundamental theory of PD source should be apparent and intelligible before conducting a PD classification study. Each PD type has its criteria, standards, reduction techniques, and different equipment damages.

A. CORONA DISCHARGE

Corona discharges imply a glow or brush discharge occurrence due to the air ionisation between the HV electrode and the ground or under HV stress at any sharp point [19] as shown in Fig.4. In other words, corona discharges also occur in the continuous partial breakdown of air under electric field stress and confined to one or both HV terminals with an area of unbroken air in between [19]. Corona discharge as an electrical discharge is brought on by the ionisation of fluid, such as the air surrounding an electrically charged conductor. Fig. 5 shows an example of a PD measurement result of

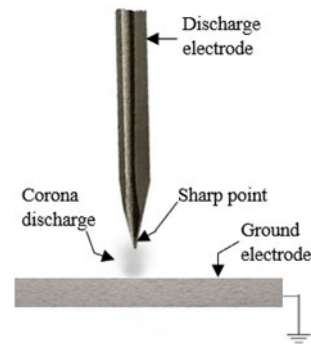


FIGURE 4. Corona discharge.

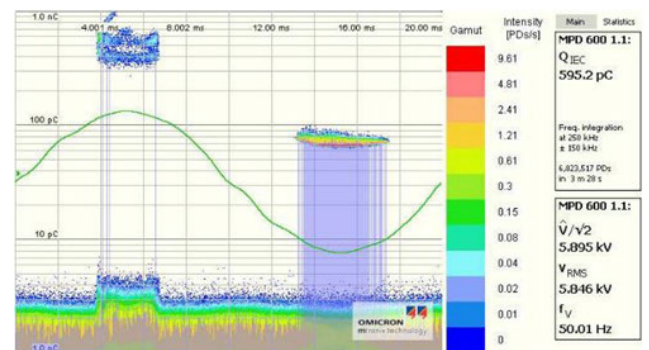


FIGURE 5. Example of measurement result of corona discharge display on sinusoidal pattern [21].

corona discharge displayed on sinusoidal pattern from the research of Boonpoke and Marungsri [21]. The pattern of corona discharge is used as an input to the proposed PD classification technique.

Many studies have reported that corona discharges are indirectly generated by the cable or its termination but may originate from the switchgear and cable/terminal hardware connection [9]. Many researchers [20], [22]–[24] used a needle or electrode as a sharp point in their experiments to analyse the characteristics of corona discharges in XLPE cables. The shape of the electrodes under HV stress enormously influences the corona discharge characteristics at low inception voltage. The sharp points of the electrode record a higher maximum charge magnitude than spherical and flat electrodes [25]. Madhar *et al.* [20] investigated four different corona configurations under DC stress from the device under test using needle-plate electrodes. They discussed the discharge patterns and physics for each configuration according to the voltage and protrusion polarity. Their results show that the only difference is in the discharge magnitude and inception voltage of the configuration, and the defects progression is similar. The electrode with a protrusion at ground plane configuration under a negative applied voltage has a relatively higher risk of corona occurrence because the streamers in the negative test voltage incept at a low voltage level and subsequently break down at reduced voltage compared with the nominal test voltage. This phenomenon proves that low

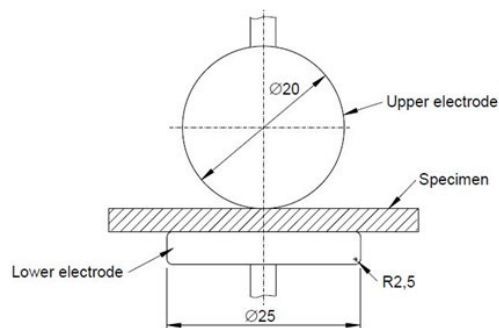


FIGURE 6. Standard test object for surface discharge [28].

voltage with an improper ground plane connection will produce corona discharge and increase the chance of equipment breakdown [20].

B. SURFACE DISCHARGE

Surface discharge occurs in a HV insulation system on the surface of a solid dielectric material due to corrosion processes. This discharge can contribute to the deterioration of the insulation surface [26], [27]. In XLPE cables, as mentioned by Isa *et al.* [3], surface discharge occurs when the tangential field component exceeds the discharge field intensity over the surface of the material. The sample test object used to detect surface discharge must comply with IEC60243 [28], that specifies test methods for determining the short-term electric strength of solid insulating materials at frequencies between 48 and 62 Hz. The behaviour of surface discharge events can be influenced by several factors, such as the type of the applied voltage and insulation and conductor materials, the configuration, humidity, and pressure [29]. According to IEC60243 [28], the test metal electrodes shall be maintained clean, smooth and free from defects at all times. This provision was proven necessary by Shi *et al.* [30] in China in their study of the surface discharge of composite dielectric in XLPE power cable joints in which they found that dielectric interface conditions largely influence the surface discharge. Their study also revealed that the XLPE cable with the cleanest surface, tight fitting and dry interfaces equipped with a layer of silicone grease exhibits the best dielectric performance.

Different insulation materials will yield different results. According to IEC60243 [28] a standard test electrode should consist of a metal sphere with 20 ± 1 mm diameter at the upper side and metal plate electrodes with 25 ± 1 mm diameter at the lower side as shown in Fig. 6. The radius of the rounded edge is 2.5 mm, and the discrepancy of the central axes between the upper and lower electrodes shall be within 1 mm. The thickness of the specimen is important because specimen results with different thicknesses are not directly comparable.

C. INTERNAL DISCHARGE

Internal discharges occur in low dielectric strength inclusions [21]. These discharges can degrade the insulation

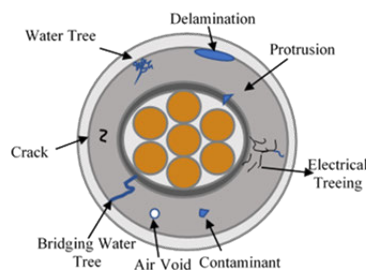


FIGURE 7. Common types of internal defects on XLPE cable.

depending on the field strength, material type, and discharge magnitude. Fig. 7 illustrates of the factors that initiate the occurrence of internal discharge in XLPE cables, such as, crack, delamination, air void and water tree. Electrical treeing and void as sources of internal discharges have received the most discussion and research interest [17], [31]–[33]. The treeing phenomena drastically reduce the lifetime of cable insulation under high-frequency AC voltage and are worse under harmonic AC voltage [34]. The effect of harmonics on the shape of electrical treeing indicates that a voltage wave with a high total harmonic distortion has features that are quite similar to high-frequency AC voltage. This phenomenon proves that various tree structures could form from a defect site in cable insulation, including bush type, tree-like and fibrillary type trees, depending on the frequency of the supply AC voltage and its magnitude [34]. Electrical treeing can grow rapidly and lead to failure of the insulation system due to the modification of the existing local electric field distribution, and failure occurs in a high electric field gradient nearly immediately after inception. Thus, the variation of PD pulse characteristics in XLPE with tree growth has been studied [35], [36] to determine the effect of the duration and magnitude of PD pulse when subjected to different intensities of average electrical stress. The shape of the electrical tree that grows from the needle tip inserted in a polymer is determined by the amplitude and frequency of the applied voltage. According to reports, failure occurs up to several days and not immediately if a relatively low average stress (<5 kV/mm) is used. In fact, faults can develop within an hour if the average stress is high, that is up to 5 kV/mm, and can develop in seconds if the stress exceeds 10 kV/mm [35], [36]. Gulski *et al.* [37] studied the transition effect from water trees to electrical trees in XLPE cables. The moment of this transition is crucial in determining the behaviour of PD because it affects the cable's insulation condition. In this research, the authors also found that the wet cable samples containing water trees of the PD activity up to hundreds of picocoulombs (pC) remained constant when the PD activity initiated. Thus, the electrical tree with a continuous AC at 50 Hz continued to grow in the second and fourth quadrants of the sine wave [37].

In 2013, Illias *et al.* [26] studied the effect of void size and the insulation thickness on the electric field of a 22-kV XLPE cable insulation system. Their results indicate that the

electric field in the void decreases as the cable insulation thickness increases. Moreover, Do Nascimento *et al.* [31] conducted a comparative experiment in 2019 to investigate the effects of electrical parameters, such as the electric field, the electric potential, the current density, and the electric field displacement due to changes in the location and size of the void inside XLPE insulated power cables [31]. They found that the location of the void inside XLPE insulated power cables has a higher impact on the electric field and the current density than the void size. These parameters are inversely proportional to the location of the void and directly proportional to the void size [31].

In summary, the defect type, size, and location inside XLPE cables are identified as threats to the good performance of electrical parameters, such as the electric field, the electric potential, the current density and the electric field displacement, if not properly managed. Continuous improvement is essential as power cables are still in use. Thus, improving the reliability of power cables through PD monitoring and detection has become a vital part of power systems, resulting in energy cost savings of 5% to 10% [31].

III. PD DETECTION TECHNIQUES

PD detection is an important monitoring tool for the avoidance of the catastrophic failures of power networks that lead to damage in electrical equipment and severe workplace safety incidents. Therefore, PD occurrence must be correctly identified and prevented through regular monitoring [27]. Since the 1980s, many different experimental methods have involved detection methods, such as electrical, chemical, acoustic and optical methods [29]. In PD detection for monitoring the performance of power cables, such as XLPE, only a few PD detection methods rely on PD pulses and frequencies. The wideband PD detection system for the low frequency range according to IEC 60270 is 30 kHz to 500 kHz, whilst the upper-frequency limit is 100 kHz to 400 kHz [10]. According to the IEEE standard, two general approaches can be adopted to detect PD pulses in installed cables, namely, off-line and on-line detection [38]. Both approaches are used to create an apparatus, like a sensor, to obtain information about the propagation of PD pulses or signals in a cable network [4].

These detection approaches have different roles and use separate voltage sources after the cable is removed from the service (i.e. off-line detection) or during the normal operation of the cable system (i.e. on-line detection) [38]. In this paper, all PD detection methods for XLPE cables in online and offline modes are reviewed and presented.

A. ON-LINE DETECTION

The on-line detection of power cables begins with sensor detection [39]. The sensor captures the signal before a wideband radio frequency (R/F) amplifier is used to amplify the signal and the analysis procedure. According to IEC60270 [10], this discharge signal appears as pulses with a duration of less than 1 μ s inside the XLPE cable. On-line

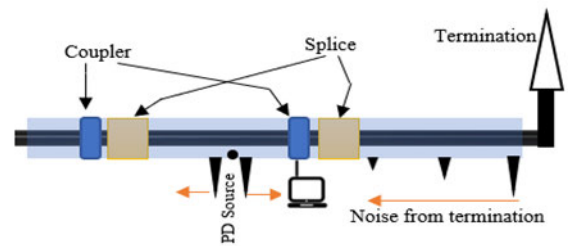


FIGURE 8. Typical test setup for on-line PD testing.

PD detection methods, also known as on-line testing methods, such as ultra-high frequency (UHF) test, high-frequency current transformer (HFCT) test and ultrasound (AE test), are options due to their suitability for practical activities [38]. However, the implementation of on-line detection must consider the sensor's sensitivity. Accurate location positioning in the existing field environment is crucial [38]. The increase in cable length and environmental noise decreases the sensor sensitivity. Thus, the mitigation of and separation from noise are the main factors of detection accuracy, measurement sensitivity and PD location prediction. These factors help avoid confusion that can influence each other. Sensitivity is expressed in millivolts (mV) or apparent charge in picocoulombs (pC) with a minimum magnitude [9]. Ghaedi *et al.* [40] mentioned that different parameters, such as currents, voltages or temperatures, could be monitored in on-line mode detection, leading to quick and accurate fault detection.

Since the 20th century, many researchers [41]–[43], have conducted in-depth studies on the different types of sensors for detecting PD signals using an on-line approach. These works proved that sensor sensitivity with a suitable bandwidth influences the sensor performance. PD signals cannot be detected if the sensitivity is low and can be distorted if the bandwidth is narrow [39]. The mistakes due to the frequency limit can be reduced if the detection bandwidth is wide [44]. Shafiq *et al.* [12] stated that the characteristics of PD signals, such as amplitude and frequency, depend on the defect size, applied voltage, material properties, the involved defect location, and the environment's condition. Sensors are placed at the end of each branched system to communicate far end data to near end devices, as illustrated in Fig. 8. The termination is connected to the power system whilst the cable remains in service with both ends connected to the system [38].

Table 2 presents the sensors' development for the on-line PD detection in XLPE cable from 1992 to 2019, as summarised in Fig. 9. Comparisons have shown the reliability and achievements of the developed methods. In the current global economic situation, focus can be given to low-cost sensor applications to reduce the production costs.

As a summary from Table 2, many advantages of the on-line detection method have attracted researchers into applying it using additional types of sensors. Different sensor parameters in on-line measurement have different impacts on the measurement results and performance. On the basis of the

TABLE 2. On-line PD detection method in XLPE based on the type of sensor.

Sensor Type	Frequency Range	Advantages	Disadvantages
Coupling capacitor sensor	10 -50 MHz	When PD pulses are picking up HF components, the REDI sensor can perform as a band-pass filter. The PD signal can be detected in the cable joint without changing the circuit[41].	The proposed sensor's performance is measured based on the experiment and not compared to the result of previous work, such as the value of magnitude charge in a specific distance of PD signal[41].
	~2 MHz	The condition of the power cable can always be monitored using the detector and, at the same time, can maintain its performance[43].	The studies do not mention how to calibrate the on-line detector and the detector's efficiency in detecting the signal[43].
VHF clamp-form sensor	1- 60 MHz	VHF clamp-form sensors can be installed at any location in the cable joint without dismantling the cable's structure and accessories[45].	At this stage, the research does not mention the noise level in the system, which can affect the sensor's sensitivity[45].
Rogowski coil (RC) sensor	~120 MHz	The well-designed RC can efficiently restrain the noise while collecting PD pulse in XLPE cables and PD signals that occur in the insulation cable are as low as 0.85pC[46].	The parameter values of R and N are taken at random without mentioning the source[46].
	~120 MHz	The detailed PD signal that cannot be detected by the basic RC due to the influence of resonance frequency can be detected by using the proposed RCAS[39].	The proposed RCAS cannot measure the noise in the PD signal, which will affect the results[39].
	~200 MHz	All the signals capture indicates the signature PD available on that cable. This is because two measurements used in this research with off-line measurement will determine the surrounding noise signal, while on-line measurement will capture all PD signals[47].	The noise signal obtained from the off-line measurement must be extracted with the efficient digital de-noising technique to ensure that the noise signal is not mixed with the real PD signal. It also requires the dismantling of all the equipment needed to perform the off-line measurement[47].
	60.7 MHz	The characteristics of the PD pulse can be studied for identifying the cause of the failure by maximising the gain-bandwidth of the coil's design[12].	The frequency band must be in the maximum range if the energy PD detected is low[12].
Ultra-High Frequency (UHF) sensor	500 MHz to 3 GHz	The UHF detection system can achieve narrowband 1.2 - 1.6GHz effectively with the sensitivity that can reach 48pC[48].	UHF sensors have a very limited distance near the PD model in the metal shield antrum[48].
	300 MHz to 3 GHz	The failure's sensitivity and appearance can be determined easily by comparing the UHF measurements and the standard PD measurement. This is because it uses two UHF sensors that can sense precisely compared to one UHF sensor[41].	UHF sensors have a very limited distance, which must be placed close to the potential failure. Minor mistakes will affect the result, which may give incorrect values during the measurement[41].
HFCT sensor	~ 20 MHz	HFCT allowed the circuit of power cables to be tested without the de-energisation process[49].	The accuracy of HFCT sensors in determining the PD pulse signal is not mentioned in the research[49].
	2 -3 MHz	The method can separate the random signals generated from unpredictable nature containing noises effectively[4].	The accuracy of the HFCT in determining the PD signals is not discussed in the research[4].
	1- 40 MHz	A quick early warning has been provided to assess the insulation condition of cables and joints[44].	The research did not clearly mention the exact distance of HFCT that needs to be installed around the grounding line of every cable joint[44].
	~100 MHz	The method is simply built using the theoretical distance between 2 Gaussian distributions with PD signal extracted accurately in noisy signal with high quality[40].	The other noises that occur near the PDs, such as non-Gaussian, random, and impulse noises like PDs, cannot be removed by this method and need an additional technique to distinguish all noises from the PD pulses[40].
	~200 MHz	The different HFCTs can be more practical and easier to compare the voltage output by using the transfer function method than FDTD methods due to physical modelling[50].	The modelling of HFCTs using the FDTD method resulting in the frequency range of the cable attenuation will be limited within 200 MHz due to the semiconductor properties that can only fit in limited frequencies[50].
HFCT and UHF sensor	3–30 MHz, 300 MHz to 3 GHz	The application of HFCT sensors to detect the PD does not depend on the power cable's size. It can even identify the PD location by supplementing the TDR technique into its practical physical design. Simultaneously, the sensitivity of UHF sensors is high and able to resist noises and other interferences[51].	HFCT sensors with the TDR technique have a high impact on noise interference when performing measurements. Simultaneously, UHF sensors have a high-frequency attenuation within a limited distance of power cables and shielding effects of the cable[51].

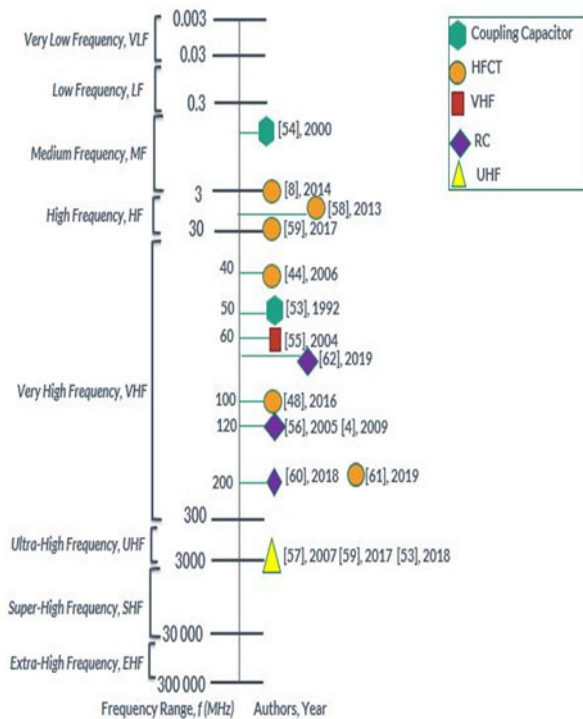


FIGURE 9. Summary of sensor development from 1992 to 2019.

duration captured inside XLPE cables, the UHF sensor is more practical than other sensors for detecting PD pulses. The focus on accuracy and efficiency has confirmed that only the RC sensor can obtain an undisturbed PD pulse because it can efficiently restrain the noise whilst collecting PD pulses in XLPE cables that occur at as low as 0.85 pC. This sensor can also perform better than other sensors with additional advantages, such as linearity, low-cost, and low inductance. The typical setup for on-line PD testing shows that the sensors' location and distance from the measuring equipment play a significant role. The sensors are placed at the end of each branched system to communicate far end data to near end devices. Then, signal processing commences to subtract the real PD signal from the noise.

B. OFF-LINE DETECTION

Off-line detection testing is carried out using a separate voltage source after the cable is removed from service [38]. This method has some advantages that can be considered. This testing can operate at different voltages whilst determining the PD characteristics and assist in identifying certain types of defects in XLPE. Given these advantages, the PD parameters can assist in identifying certain types of defects in XLPE. The PD parameters, such as PD inception voltage, PD extinction voltage, and the PD magnitude versus the voltage plot (*q* vs. *V*), can be used during the measurement or testing procedure [38]. In contrast with that in the online approach, the cable in the off-line test is isolated and disconnected from the network at both ends, as shown in Fig. 10. A voltage

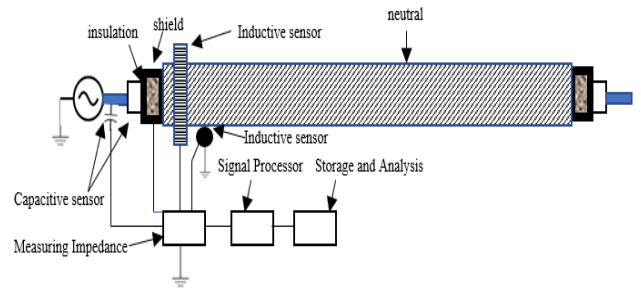


FIGURE 10. Typical test setup for off-line PD testing.

source and a sensor are connected at the ends with open remote ends.

In terms of sensitivity, like online detection, off-line detection also requires high sensor sensitivity, especially if the PD source generates low-magnitude pulses. The magnitude and the repetition rate increase with the excitation voltage. Thus, an inadequate detection sensitivity may mask the existence of serious defects with low PD magnitudes [9]. Table 3 shows the advantages and disadvantages of off-line PD detection methods in XLPE based on different types of sensors.

As a summary from Table 3, the measurement using off-line detection must consider several factors that can affect the PD signal, such as the cable parameters, the length of cables, and the distance between the cables and the sensor, to prevent the performance of the system from being compromised whilst taking measurements. Furthermore, the data from off-line measurement is captured first, and the analysis is performed later. Thus, off-line detection may be more time-consuming than on-line detection.

Therefore, the type of sensor used in detecting PD signals plays an important role in analysing the pulse propagation in a cable and constituting the PD signal characteristics. Meanwhile, a good sensor material is important for developing a preferable sensor for PD detection, especially the characteristics of the material itself that influence the performance of the sensors.

Thus, the sensor characteristics must be the priority of studies, especially the sensor sensitivity in low- and high-range PD signal frequencies. The PD signal resulting from a good sensor can improve the understanding of how to protect the cable insulation from breakdown. Obviously, on-line techniques are the best solution for PD detection activities. In the off-line mode, PDs may occur between intervals as the detection of PDs involves discrete intervals [40].

Consequently, insulation failures increase, and the condition monitoring system becomes inefficient in diagnosing the PD signal. However, additional procedures, such as PD recognition algorithms, can be used to eliminate background noise. Thus, off-line measurements are required to establish the noise levels and provide a filtration pattern. The pattern can be used to remove unwanted signals and assess pure PD signals.

TABLE 3. Off-line PD detection method in XLPE based on the type of sensor.

Sensor Type	Frequency Range	Advantages	Disadvantages
VHF capacitive coupler sensor	30 - 300 MHz	Capacitive couplers can be used to get reasonable sensitivity even though the measured PD signals have an attenuation caused by the existence of the insulating gap[52].	The cable metal cover length must be removed in a certain size to implement the capacitive coupler[52].
Very Low Frequency (VLF) sensor and RC sensor	0.05 - 1 Hz	A noise signal with hidden PD activity has been filtered by RC within 144kHz to 1GHz. While PD pulse has been extracted using Discrete Wavelet Transform DWT-based de-noising methods, which can extract PD pulses from noised signals[53].	The characteristics of damaged cable joints are not discussed in this study, so additional criteria of the proposed RC are not discussed[53].
HFCT sensor	~20 MHz	The results obtained from HFCT can display a clear waveform compared to a conventional tool, in which the waveform generated is hard to understand[24].	The sensitivity of HFCT in detecting electric charges is lower compared to the conventional tool. HFCT only can detect the electric charges in pC when the values are high enough[24].
UHF sensor	~300 MHz	The chosen inductive-line UHF coupler offers low impedance to UHF signals and high impedance to the power frequency[54].	The cables' defects must be chosen in various locations to identify the accuracy of the UHF sensor[54].



FIGURE 11. Steps for PD classification.

IV. PD SIGNAL CLASSIFICATION

The relationship between the PD patterns and the aging process of the insulating materials of XLPE cables has attracted researchers [55]–[57] into classifying PDs according to their type. Various methods and techniques have been proposed in parallel with technology advancement. Each type of PD defect has its degradation characteristic. Thus, identifying the correlation between the defect type and the PD pattern is important in investigating the quality of the material insulation. According to [57], an intelligent classifier is crucial for classifying the PD source using the measured PD characteristics because the direct inspection of the measured PD patterns is complex. Several steps must be considered in obtaining a good PD classification result. These steps start with PD measurement, including abstracting the PD pulse using on-line or off-line detection. The next step is feature extraction for identifying the PD patterns. The last step is the development of a PD classifier using the data extracted from the PD patterns. The process flow of the PD classification is illustrated in Fig. 11. PD detection and measurement are discussed in Section III, where a PD detector, such as sensor and coupling devices, is used to obtain the PD data.

A. FEATURES EXTRACTION

Feature extraction plays an important role in pattern recognition. The consistency of the extracted features will affect the efficiency of the classification algorithm, which is similar to the PD pulse phase analysis. Several techniques can be adopted for feature extraction, such as statistical data analysis, signal processing, image analysis, information retrieval,

bioinformatics, data compression, computer graphics, and machine learning. The extracted features, such as the statistical and phase-resolved partial discharge (PRPD) pattern characteristics, are used to build classification algorithms [57]. The major issue associated with PD signal measurement is the heavy contamination by noise that results in decreased efficiency in PD patterns detection. Most of the statistical operators are derived from PD distributions and applied to classification procedures to reduce the difficulty of the recognition process [58]. Reducing the size of the input data for real-time fault classification is important to reduce the computational burden because it can also reduce the bandwidth.

Numerous feature extraction techniques have been proposed, including the time-resolved partial discharge (TRPD), the phase-resolved pulse sequence (PRPS), and the PRPD, mainly including Fourier transforms, wavelet transforms, Hilbert transforms, the decomposition of empirical mode, the transformation of S parameters, fractal parameters, and polar coordinate transformation. The PD patterns of defects can be identified if some discriminative features are extracted from the raw data [59]. The details of these extraction techniques are presented in the next section.

1) STATISTICAL TECHNIQUES

Given that PD is a random phenomenon for reliable statistical analysis to identify PD patterns, sufficient PD samples must be captured [60], [61]. Statistical features, like mean, variance, kurtosis, skewness, cross-correlation factor (CCF), phase asymmetry, discharge asymmetry, and modified CCF, are estimated for the number of PD events (n) against the phase angle (ϕ), ($H_n(\phi)$), and the PD charge magnitude (q) against the phase angle (ϕ), the ($H_q(\phi)$) distributions [57]. The different sizes of cavity PD patterns in XLPE were compared by Dessouky et al. [55] using statistical features, as shown in Fig. 12.

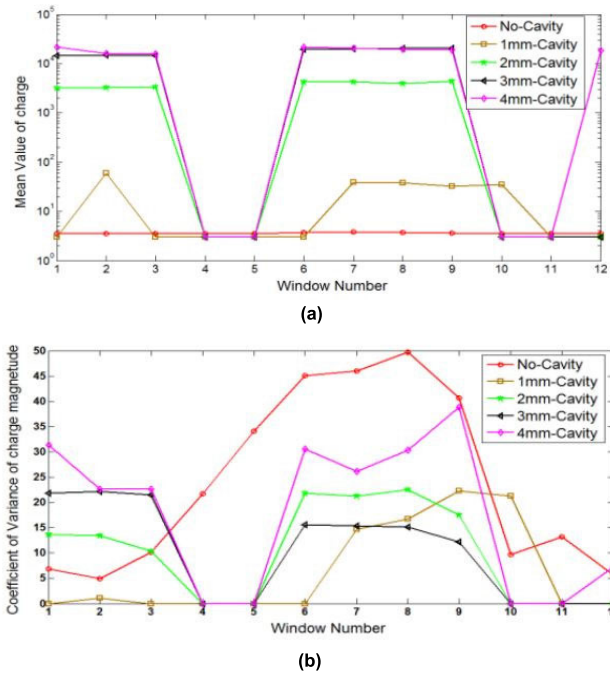


FIGURE 12. Examples of parameters of statistical features: (a) mean and (b) coefficient of variation [55], [56].

The mean, the standard deviation and the coefficient of variation are better than the maximum value, skewness, and kurtosis statistical features when used to classify the defective cable models [56]. The effectiveness of feature extraction can be improved by combining the calculated PD parameters, such as the mean apparent charge, the pulse repetition rate, the average discharge current, and the quadratic rate, with the statistical features [62]. Jineeth *et al.* [57] defined the statistical features in their studies as summarised in Table 4.

2) PHASE RESOLVED TECHNIQUE

One of the earliest phase-resolved techniques used in PD studies is a PRPD technique known as the PRPD pattern (1995). The use of PRPD in analysis is beneficial for pattern recognition and has been widely used to diagnose PD defects in an insulation system with a noise environment [63]. Compared with time-resolved features, such as TRPD, which is unsuitable for pattern recognition, the effect of signal propagation path and noise interference is quite great [64]. A classifier is difficult to develop without PRPD data because the data extracted from the PRPD can be easily used by a machine learning model.

Karimi *et al.* [61] used three main characteristics of PRPD: maximum charge (q_{max}), average charge (q_{mean}), and the total number of PDs (q_n). These characteristics are calculated in predefined window intervals along the 360-degree AC power cycles. As the PD source is mainly in phase form, the parameters in each interval must be determined. These characteristics in the PRPD technique along with the statistical operators can increase the number of features whilst, developing a new PD classifier as shown in Fig. 13. Statistical variables, including

TABLE 4. Parameters of statistical features [57].

Parameters	Function	Equation
Mean	Average of all pulses over both half cycles.	$\mu = \frac{\sum_{i=1}^N x_i}{N}$ <p>N is the number of samples. x_i is the charge magnitude of the ith sample.</p>
Variance	Describes how much a group of numbers is spread out.	$\sigma^2 = \sum_{i=1}^N (x_i - \mu)^2$
Kurtosis	Indicates the sharpness of the distribution.	$k_\mu = \frac{\sum(x_i - \mu)^4}{\sigma^4} - 3$
Skewness	Indicates the symmetry of distribution concerning the normal distribution.	$S_k = \frac{\sum(x_i - \mu)^3}{\sigma^4}$
Cross-correlation factor (CC)	Evaluates the difference in the shape of distributions.	$CC = \frac{\sum xy - \frac{\sum x \cdot \sum y}{n}}{\sqrt{[\sum x^2 - \frac{(\sum x)^2}{n}][\sum y^2 - \frac{(\sum y)^2}{n}]}}$ <p>x is the mean discharge magnitude in the positive half of the voltage cycle. y is the mean discharge magnitude in the negative half of the voltage cycle. n is the number of phase positions per half cycle.</p>
Discharge Asymmetry	The quotient of the mean discharge level of the $Hnq(\phi)$.	$DA = (Q^-n/N)/(Q^+n/N)$
Phase Asymmetry (ϕ_A)	It studies the difference in the maximum pulse of the $Hnq(\phi)$.	$\phi_A = \phi^-_{max} / \phi^+_{max}$
Modified cross-correlation factor (MCC)	Evaluates the differences between discharge patterns in the positive and negative halves of the voltage cycles.	$MCC = D_A \cdot \phi_A \cdot CC$

skewness, kurtosis, asymmetry, and the cross-correlation of the phase-charge-number of PD (Φ -q-n) patterns, have been used in many studies [61], [61], [65], [66]. Furthermore, these researchers also used three other vectors, namely V_{max_i} , as a vector of q_{max} , V_{mean_i} as a vector of q_{mean} , and V_{n_i} as a vector of q_n for the i^{th} half cycle. Each vector contains phase windows, W elements (where W is the phase windows), as shown in (1). W is 360 and 36 if the window interval is 1° and 10°, respectively, along the cycles, C . The PRPD matrix can be determined with the value of C as the row and $(3 \times W)$ as the column.

$$W = \frac{360}{window\ interval} \tag{1}$$

Raymond *et al.* [67] stated that the PRPD pattern could be characterised using two fractal features, namely, fractal dimension, and lacunarity, which are measured using the box-counting technique. Fractal characteristics can be incorporated in PD recognition because they explicitly characterises

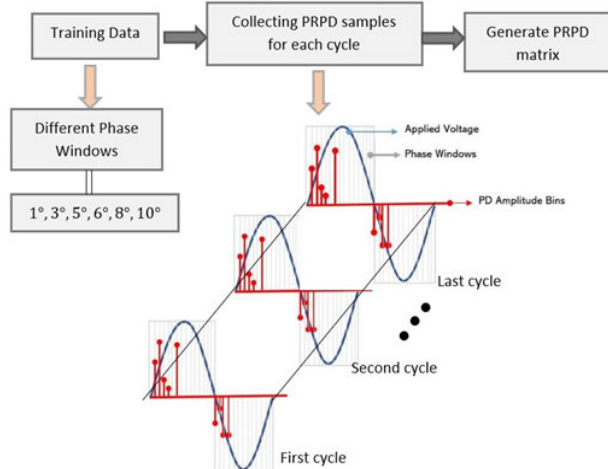


FIGURE 13. Characteristics of PRPD feature extraction process for each cycle.

the PRPD pattern [67]. The PD data are arranged into three column matrices, namely, phase, magnitude, and pulse count, like the PRPD format. However, no standard duration can be referred to for generating a single PRPD. Thus, Xin *et al.* [68] investigated the effects of an extremely short duration in PRPD on the PD classification accuracy. A duration interval of 1 s to 15 s was selected to test the overall system robustness to recognise the PD source. The result shows that the accuracy of PD classification is unaffected by the PRPD duration. However, for XLPE cable joints, a longer PRPD duration is recommended to improve the classification accuracy in terms of practicality [68].

The other phase-resolved feature is the PRPS. According to Lim *et al.* [69] the PRPD pattern data of various facility defects are acquired through the diagnosis of underground power transmission cables. However, because the PRPD data storage structure and the pulse generation information are destroyed over time, reconverting to a 3D PD pattern (i.e. PRPS) is impossible. To generate the pulses based on the PRPS pattern using the existing PRPD pattern and input the pulses into the device to perform the defect judgement output test, a PD pulse generator must be created based on simulated PRPS data. The development of a PD pattern generator that can generate pulses based on PRPS data and an algorithm that converts existing PRPD pattern data to PRPS pattern data were studied by Lim *et al.* [69] to solve the issue. Their study shows that PRPS and PRPD can be performed together with a new technique and equipment development.

3) PRINCIPAL COMPONENT ANALYSIS

The principal component analysis (PCA) introduced in 2007, known as the Karhunen–Loève (K–L) method, can also be used to filter out important factors from the large data [70]. This method can be transformed to a lower dimension without reducing the space, with minimal information data loss. Like other features, the concern is on the parameters

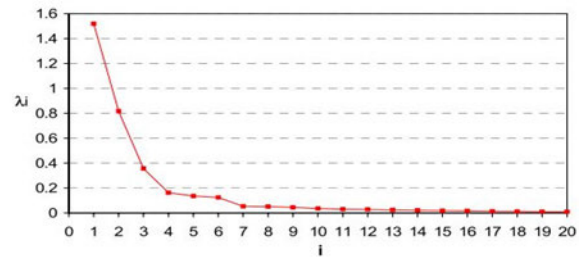


FIGURE 14. Scree plot from large to small of the sorted eigenvalues [70].

used during calculation, such as the number of principal components required to obtain an accurate depiction of the original data [67]. Data can be arranged into three column matrices of phase, magnitude and pulse count similar to the PRPD format. The best number of principal components implies that increased data accuracy can be obtained. Thus, to obtain the best number, Babnik *et al.* [70] introduced a scree plot in 2007, as shown in Fig. 14. According to Raymond *et al.* [67], two situations exist in PCA. In the first situation, the positive and negative of charge magnitudes are split into four distributions and phase-divided into two quadrants with 180 degrees. In the second situation, the positive and negative of charge magnitudes are split into six distributions and divided into four quadrants with 90 degrees.

4) FRACTAL FEATURES

The next extraction feature suitable for natural phenomena with complex shapes is the fractal features. Fractal features are suitable for PD recognition because they can directly characterise the PRPD pattern [71]. Two types of fractal features can be calculated using the box counting technique: fractal dimension and lacunarity [67]. The fractal dimension can be computed from an image surface and can measure the coarseness of the surface. However, given different surface values with the same fractal dimension, additional methods, such as ANN, must be used to support the fractal dimension features [67]. Duan *et al.* [72] proposed four fractal dimensions that represent the grey image used in PD pattern recognition as a discharge fingerprint. If the grey value on the image is 0, then the insulation is in good condition, no discharge phenomenon occurs, and it can be ignored in the calculation. The result shows that all dimensions provided can be used as a recognition feature quantity, accurately obtaining the PD classification result. However, this feature is unsuitable for use as an input for the PD classifier in signal processing due to the strong mathematical theory support required. The speed of convergence is low so that this dimensions can easily decrease to local minimum values [72].

B. PD PATTERN RECOGNITION METHOD

Since the 1960s, PD fault issues have been an interesting topic among researchers, especially in assessing the cables' condition in service and identifying the type of defects in

cables. These two topics have expanded yearly based on the types of methods used, such as statistical learning, artificial intelligence, and fuzzy logic. In this section, each PD pattern recognition method is reviewed in terms of repeatability, recognition accuracy, and recognition speed to determine which methods have a good performance.

1) SUPPORT VECTOR MACHINE

SVM was introduced in the 1960s on the basis of statistical learning theory. In 1995, V. N. Vapnik [73] proposed the first application in pattern recognition. SVM presents great benefits for a small sample quantity and nonlinear and high dimensionality pattern recognition issues due to the application of kernels in the system, enabling SVM to perform in different tasks [73]. The SVM algorithm kernel uses a set of mathematical functions that take data as input and transform it to the required form. Many types of kernels based on their function exist, such as polynomial, Gaussian, Gaussian radial basis function (RBF), Laplace radial, hyperbolic, sigmoid, Bessel function, ANOVA radial basis and linear spline. In 2013, Sarathi *et al.* [74] investigated the Gaussian RBF kernel based on SVM to classify PD. The RBF kernel function provides a better result for SVM than the other kernels, with an overall classification rate of 99.76%.

SVMs have been applied by many researchers [66], [72], [75] since their introduction for classification and analysis purposes, especially for the repeatability and accuracy of the method. SVM can classify inputs into two classes; if more than two classification groups are required, multi-level SVM is needed [67]. The category sample of PD data was classified during multi-level SVM training as one class and the other samples as another class [67]. Serttaş and Hocaoğlu [76] proposed multi-class SVM to classify PD defects with additional statistical features as a parameter of the SVM. The best part of the research is that no noise filtering was applied, and all the data used were based on the measuring signal desired in the signal processing technique. The method's accuracy was measured based on four conditions, with the combination of SVM and statistical features obtaining a higher accuracy of 94% than the others [69]. However, the repeatability of the result is not mentioned in the paper. Raymond *et al.* [67] investigated the SVM performance using three features, namely, statistical, fractal, and PCA, under a noisy environment in five different cable joint defects. The performance of these features varies as the input feature combination has a noise tolerance. Statistical features exhibit a lower accuracy as the noise duration increases than the fractal feature and PCA (i.e. 47.1%, 57.1% and 73.9%, respectively). Overall, research indicates that SVM performs better in noise-free conditions than in noise conditions.

Furthermore, Duan *et al.* [72] reported the higher accuracy of their proposed SVM (95%) than the traditional SVM. In this work, M-ary classification theory is used to expand SVM into multi-class classifiers. Thus, to improve the SVM performance, a genetic algorithm (GA) is used to optimise

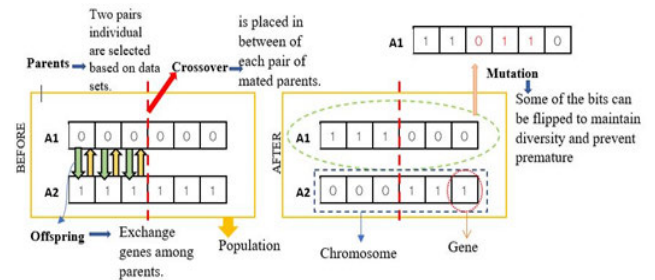


FIGURE 15. Operators used in GAs to compute the next generation from the actual one.

SVM parameters. The result shows that the accuracy of PD recognition is further improved, and the parameter optimisation of SVM exhibits improved classification accuracy [72]. The application of SVM is continuously improving.

2) GENETIC ALGORITHM

GA is frequently employed to develop high-quality solutions to optimisation and search problems by using biologically inspired operators, including mutation, crossover and selection, as illustrated in Fig. 15. This algorithm inspired by Charles Darwin's theory of natural evolution [77] has been used by researchers in various fields, including HV cables [77], [78], to optimise pattern recognition and improve the performance of existing systems. Rizzi *et al.* [79] investigated an automatic approach based on the GA's ability to optimise a diagnostic system for the recognition and identification of PD pulse patterns in the terminations and joints of solid dielectric extruded power distribution cables. This approach is used for PD source identification in cables and other electrical power equipment by reducing the system complexity whilst improving the diagnostic performance. Three hundred measurement data have been used and show that GAs can achieve 100% accuracy on the test sets. However, to achieve the desired target, GAs have been replicated with the same analysis by replacing an exhaustive one with a new dataset. Although GA is faster than other algorithms, it is not a complete algorithm because it does not always find suitable solutions.

The work published by Fresno *et al.* [78] describes GAs as a strategy for separating pulse sources with promising experimental findings based on spectral power ratios.

The selection, reproduction, crossover and mutation of the elements that make up the numerous solutions to the objective function are used in this meta-heuristic method. Based on their research, the intervals of the calculation-based GAs can produce a larger value of parameters, providing a satisfactory classification without any human supervision compared to the manual calculation value. To define the intervals, GAs do not need an expert study on the shape of the spectra. However, this algorithm still has a constraint of turning the fitness value to 0 when the mutations or crossovers send the frequencies out of the bounds defined by the constraints, ignoring the next generation [78].

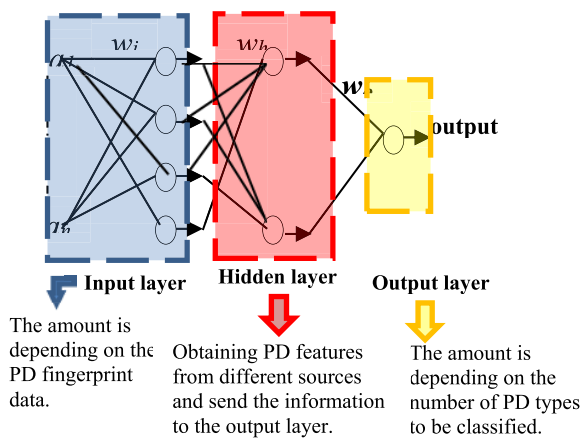


FIGURE 16. Multilayer ANN and its function.

3) ARTIFICIAL NEURAL NETWORK

Since the 20th century, ANN has been attracting the interest of many researchers in various fields for studies and applications, such as signal-processing tools, control systems, and image processing. According to PD faults studies, ANN is suitable for PD classification because it is unaffected by small input changes. That is, ANN can still make the right decision even with a difference in input data from the input used during the training procedures. ANN also has a great potential in areas such as pattern recognition, encouraging the application of PD pattern diagnosis [80]. However, to obtain the best ANN performance in PD recognition, accurate information must be provided to the network. ANN can be constructed and designed with at least one layer of input, one hidden layer, and one output layer, with every layer connected to the following layer. A multilayer neural network (NN) and its mechanics [65] are illustrated in Fig. 16.

Many NN types have been proposed in previous works, such as the feed-forward back propagation (FFBP) neural network, the RBF, recurrent neural network and convolutional neural networks. However, the most commonly used learning mode in ANN is the FFBP [67]. The FFBP belongs to the supervised learning category and is trained in a forward backward process consisting of three layers: the input, hidden, and output layers [67].

The weights and biases are initialised into small random values in a forward way. The neuron output in each layer is computed using an activation function in the feature vector [67]. To avoid any restraint whilst running the system, at least two input features are required for PD classification [67]. Unlike other works that are usually performed in a noise-free environment, Raymond *et al.* [67] investigated a multilayer feed-forward ANN in a noisy environment using 15 neurons at the hidden layer and the scaled conjugate gradient backpropagation training function. PCA, statistical, and fractal features were used to train the classifiers to compare the accuracy and training speed as the feature size changes. Their finding proves that the increase in feature size is unaffected by the training speed of ANN that remains constant

as the size increases. However, in a high noise environment, the PCA features with ANN are recommended for better classification results [67].

Meanwhile, Majidi, and Oskooee [81] proposed three types of ANN, namely, FFBP, RBFNNs, and the NN pattern recognition toolbox (nprtool), to recognise the patterns of the processed data. Their study is quite complicated, measuring the performance of three types of ANN in five scenarios. However, the proposed methods have simple calculations that are not time-consuming. They found that the high number of input parameters of ANN plays an important role in discriminating the PD classes in five scenarios. The correlation factor in the FFBP network, the error value in the RBF network and the classification percentage in nprtool are 0.9867, 0.0001, and 96.4%, respectively.

Moreover, ANN was used by Figueroa *et al.* [82] to develop a benchmark for identifying the quality of XLPE cable insulation by classifying the PD types in a short duration at low cost. The correlation between the defect type and the PD patterns is important in identifying the different types of PD. Each type has unique characteristics for assessing the quality of insulation. A study proposed a probabilistic NN Bayesian modified (PNNBM) method with a large amount of data to determine a solution within a short period [82]. The application of PNNBM was published in 1989 by Donald F. Specht in his research, 'Probabilistic Neural Network'. This publication introduced a PNN that can estimate decision limits or nonlinear decision surfaces through an optimal Bayesian approach [82]. This work also found that the increase of the feature size or input data is unaffected by the performance of PNNBM, and the accuracy can be maintained.

Other works published by [83] used feature pruning using the IndFeat and ReliefF algorithms to reduce the input feature size for the easy implementation of ANN as a PD classifier [83]. The algorithms can reduce the size of the input feature by eliminating the most insignificant input features. When the input data is reduced to 18.75%, the accuracy of the ANN accuracy is indirectly reduced by 1%. Thus, if 50% feature reduction occurs, the accuracy of the ANN is reduced by 1% to 3% only, proving that whenever a feature algorithm is used to reduce the data size, the accuracy of ANN is affected by not more than 5% of data reduction.

4) ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

Since the 1940's, after the analysis of PD started and have been more intensively studied worldwide, many recognition methods have been proposed, including adaptive neuro-fuzzy inference system (ANFIS) [84]. This method combines NNs and fuzzy systems to determine the best fuzzy parameters [67]. Fuzzy parameters cannot be select manually but can be done using a NN. Prior to the fuzzy scheme training in ANFIS, the fuzzy structure must be constructed using fuzzy logic. The first fuzzy modelling was introduced by Takagi and Sugeno in 1985 [85]. ANFIS is a great tool for mapping PD patterns to the PD types using 'If-Then' rules.

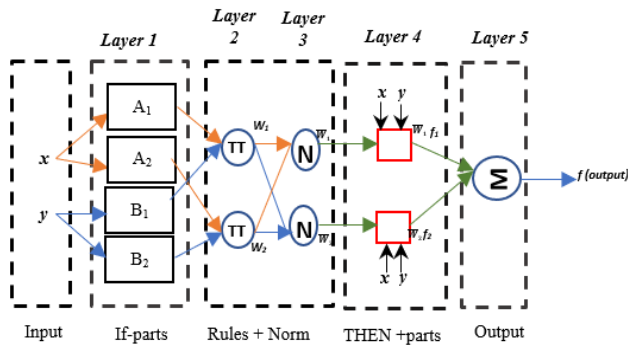


FIGURE 17. Characteristics of ANFIS.

The rules generated by the decision tree have five important layers, as shown in Fig. 17 [85]. The first layer is called adaptive nodes whose output becomes the input to the second layer and known as the fuzzy membership grade. The second layer has a constant node that acts as a multiplier for incoming signals and determines the rules’ firing strength. The second layer’s output that has a trigger strength is received by fixed nodes in the third layer to normalise the firing strength. Then, another adaptive node in the fourth layer produces the first order polynomial and the normalised firing power. Lastly, all output signals from the previous layers are summarised by a fixed node in the fifth layer [67]. Examples of the rules:

Rule 1: If x is A1 and y is B1, then $f_1 = p_1x + q_1y + r_1$

Rule 2: If x is A2 and y is B2, then $f_2 = p_2x + q_2y + r_2$

Chalashkanov et al. [86] developed pattern recognition by using 15 statistical parameters for ANFIS input comprising a discharge fingerprint to discriminate between internal PD pulses. The number of input features becomes six after the discriminant analysis. The two parts of measurement data are split into 22 and 8 samples to generate and verify the performance of ANFIS, respectively.

They achieved a classification accuracy of 95.8%, which is better than that in the previous case of a classifier with 15 input features. Redundant data were removed through discriminant analysis, improving the capability of ANFIS whilst increasing its accuracy. Fard et al. [87] investigated ANFIS in 2010 based on the Sugeno fuzzy model for PD defect classification in an insulation area using the input data from statistical features. The two models were compared with 33- and 12-input models and to each other in terms of accuracy of feature selection in providing features data to the system. They found that the accuracy of a 12-input model (93%) is higher than that of the 33-input model (84%), proving that the features selection in the system can influence the ANFIS system’s accuracy.

In summary, the classification of PD data based on PD types is the best approach to overcome the issue because it can help identify the root cause of PD activities and estimate the PD harmfulness. Table 5 summarises the performance of each PD classification method reviewed. The selection of network types and feature parameters has a high impact on recognition and speed accuracy. High accuracy with fast

TABLE 5. Summary of performance of PD classification method.

Author	Classification Scheme	Features Extraction	Data Repeatability	Accuracy of recognition
[57]	ANN SVM	PRPD, statistical	low	95.49% 99%
[61]	DBN ANFIS SVM	PRPD, statistical	high	98% 70% 75.7%
[65]	PNN	PCA	high	>98%
[72]	GA-SVM	Fractal dimension	low	96.5%
[86]	ANFIS	Statistical	high	95.8%
[87]	ANFIS	PRPD	high	93%
[88]	DBN	PRPD	high	94.8%

recognition speed is the best solution to classifying the PD and reducing the possibility of system break down.

V. CONCLUSION

PD fault is an important cause of insulation degradation and electrical equipment breakdown. The PD activities in XLPE cables can be influenced by several factors, such as the type of applied voltage, the insulation material, the conductor material, humidity, and pressure. Accurate PD fault type identification is crucial because by knowing the PD type in XLPE cables, the correct preventive or corrective maintenance can be performed to avoid breakdown.

The types of PD defects that could occur in XLPE cables were reviewed. The sources that activate the PD activities are discussed. The setup for on-line and off-line PD measurement for XLPE cables in previous works is presented. Moreover, the technologies development on PD detection methods for HV cables were reviewed and summarised. The review reveals that the on-line method is preferred by numerous researchers although the measurement is deficient in terms of sensitivity.

The PD detection sensor with high sensitivity utilised in on-line or off-line methods is a vital in accurately detecting PD signals in a noisy environment. The extraction of different features is discussed to compare and identify the features that perform well in terms of eliminating the noise in PD signals and reducing the data input size for the PD classifier. Furthermore, the classification theories of PD patterns based on machine learning, such as SVM, ANN and fuzzy logic, obtained by previous researchers are discussed and compared in terms of data repeatability, accuracy of recognition, and recognition speed. Overall, the following conclusions can be drawn:

- (i) PD signals can be detected accurately by using on-line detection to achieve a meaningful response effect. However, off-line detection can also be used but should be supported with additional procedures, such as PD recognition algorithms. Off-line measurements are required to establish the noise levels and provide a filtration pattern. The patterns can be used to remove unwanted signals and analyse pure PD signals.

- (ii) On the basis of the duration captured inside XLPE cables, the UHF sensor is more practical than the others for detecting PD pulses. In terms of perfect linearity, low-cost, and low inductance that can quickly respond to the currents, the RC satisfies all the mentioned requirements. The RC sensor can also improve the accuracy and efficiently restrain the noise whilst collecting PD pulse in XLPE cables in wide current ranges.
- (iii) The best PD classification approach in terms of accuracy and repeatability is ANN. The feature reductions in the ANN classifier do not significantly affect the accuracy.

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