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Multiple Partial Discharge Signal Classification Using Artificial Neural Network Technique in XLPE Power Cable

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ABSTRACT

According to partial discharge (PD) damage in the electrodes that are not entirely bridging, the presence of PD in the high voltage (HV) power cable might lead to insulation failure. PD defects can damage cross-linked polyethylene (XLPE) cables directly, which is one of the most critical electrical issues in the industry. Poor workmanship during cable jointing, aging, or exposure to the surrounding environment is the most common cause of PD in HV cable systems. As a result, the location of the PD signals that occur cannot be classified without identifying the multiple PD signals present in the cable system. In this study, the artificial neural network (ANN) based feedforward back propagation classification technique is used as a diagnostic tool thru MATLAB software in which the PD signal was approached to determine the accuracy of the location PD signal. In addition, statistical feature extraction was added to compare the accuracy of classification with the standard method. The three-point technique is also an approach used to locate PD signals in a single line 11 kV XLPE underground power cable. The results show that the statistical feature extraction had been successful classify the PD signal location with the accuracy of 80% compared to without statistical feature extraction. The distance between PD signals and the PD source affected the result of the three-point technique which proved that a lower error means a near distance between them.

1. Introduction

The high voltage (HV) distribution network currently has the essential infrastructure of an expensive underground power cable system. The insulation of HV equipment had deteriorated due to the cumulative effects of electrical, chemical, and mechanical stressors caused by partial discharge (PD) [1]. The presence of PD in the HV power cable can cause insulation breakdown due to PD damage in the electrode that is not fully bridging [2,3]. The abundance of energy resources in Malaysia offers

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possible alternatives to generate electricity and it is important to overcome any electricity-related issues especially involving electrical cables [4]. Since energy resources are a crucial component of global politics and economics, technical advancement in energy systems is actually a crucial and unavoidable issue that scholars must address [5]. In HV cable systems, PD mostly occurs at the cable joints due to poor workmanship during the cable jointing, ageing or being exposed to the surrounding environment [6]. For the operation and maintenance of power equipment, accurate and effective identification and evaluation of PD are vital [7-9].

PD analysis enables the detection of critical defects and assessment of the condition of the insulation system. Several methods for classifying and identifying PD typologies, or the types of sources that generate PD, have been developed by many researchers. In this study, the simulation had been carried out for the measurement of PD in a single line 11 kV power cable by using the electromagnetic transient program-alternative transient program (EMTP-ATP) software with multiple PD signals.

PD signal based on ANN classification technique is used as a diagnostic tool that can give valuable information about the condition PD signal by using MATLAB software. ANN is one of the technologies of Artificial Intelligence (AI) that driven technologies to embrace the efficiency and flexibility of production in the industry 5.0 [10]. In addition, statistical feature extraction was added to compare the accuracy of classification with the standard method. The three-point technique is also an approach used to locate PD signals in a single line 11 kV XLPE underground power cable.

2. Literature Review

PD can be classified into three main types which are internal discharge, surface discharge and corona discharge [11]. Internal discharge happens when a defect of closed volume within a solid or liquid insulating material occurs. The electric field in the void will be higher than the surrounding insulating medium under the operating voltage because the dielectric constant of the gas in the void is lower than the insulating medium [12]. While surface discharge mainly occurs between the inner primary insulators cable and winding insulation interfaces. It also can happen when the material surrounding the XLPE cable has reduced the permeability than the XLPE cable itself. It can develop at the end of the XLPE cable if the cable termination is not graded correctly [13]. Different with corona discharge which is as an electrical discharge that brought on by the ionisation of fluid, such as the air surrounding an electrically charged conductor. Corona discharges 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 [14].

There have four types of the PD detection methods which optical detection, acoustic detection, chemical detection and electrical detection [15,16]. Table 1 shows the summary of detection of PD in the power cables.

Various methods and techniques have been proposed in parallel with technology advancement such as Support vector machine (SVM), ANN and Adaptive Neuro-Fuzzy Inference System (ANFIS). Identifying the correlation between the defect type and the PD pattern is important in investigating the quality of the material insulation. According to Jineeth *et al.,* [22], 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. Table 2 shows the difference between SVM, ANN and ANFIS.

Table 1
Summary of previous work regarding the detection method using in PD detection

Detection Method	Theory
Optical	I. Two detection methods which optical signal produced by PD and optical beam caused influenced by PD signal [17] II. Advantage: the external electromagnetic noise can be controlled by using fiber-optic. Thus, this method can gain the electromagnetic interference (EMI) resistance and at the same time can be presented to the conventional PD detection technique. III. Disadvantage: The optical transmitter needs a working power supply and expensive on-site measurement costs.
Acoustic	I. The theory of the acoustic detection method is that the wave induced by a small explosion or micro-crack is generated in the insulator [18]. II. Advantage: EMI-free, non-invasive, quick installation, and sensor replacement. Inside the transformer tank, the acoustic detection system can detect up to 350 kHz in all frequency ranges [19]
Chemical	Disadvantage: The detection of PD using DGA does not offer the PD function and is complicated [17]
Electrical	I. amplitude: low [20] II. current pulse: short duration (nanosecond to microsecond) III. Advantage: excellent in capturing the electrical signal compared to others. IV. Different types of traditional current sensors are suggested to detect either off-line or on-line PD signals [21].

Table 2
Difference between SVM, ANN and ANFIS

Classification Method	Theory
SVM	SVM can classify inputs into two classes which are one class (during multi-level SVM) and the other sample as another class. The multi- level SVM is needed if more than two classification group are required [3].
ANN	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. ANN is unaffected by small input changes; thus, it is suitable for PD classification. A difference in input data from the input used during the training procedures is not an obstacle for ANN to make the right decision.
ANFIS	This method combines neural network and fuzzy systems to determine the best fuzzy parameters [23]. Fuzzy parameters cannot be selected manually but can be done using a neural network. Prior to the fuzzy scheme training in ANFIS, the fuzzy structure must be constructed using fuzzy logic.

The classification of PD types based on PD data 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 3 shows a summary of classifier used in PD signal classification.

Table 3
Classifier used in PD Signal Classification

Classifier	Previous Research Work
SVM	The Gaussian RBF kernel based on SVM is investigated to classify PD. With an overall classification rate of 99.76 percent, the RBF kernel function performs better for SVM than the other kernels [24]. The proposed SVM has a high accuracy (95%) than the traditional SVM. In this work, M-ary classification theory is used to expand SVM into multi-class classifiers by using a genetic algorithm (GA) to optimise and improve the SVM performance [25]. The research indicates that SVM with statistical features performs better in noise-free conditions than in noise conditions compared to fractal and PCA [3].
ANN	The finding proves that the increase in feature size is unaffected by the training speed of ANN that remains [3].

	ANN was used to develop a benchmark for identifying the quality of XLPE cable insulation by classifying the PD types in a short duration [26]. I. ANN is said to be easy to implement as a PD classifier when using the IndFeat and ReliefF algorithms to by eliminating the most insignificant input features [23].
ANFIS	I. Pattern recognition using 15 statistical parameters have been developed as ANFIS input comprising a discharge fingerprint to discriminate between internal PD pulses [27]. II. Researcher found that the comparison between 12- and 33-input models providing features data to the system have 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 [28].

3. Methodology

This project is divided into three steps which are modelling the PD measurement using EMTP software, classification of PD signals using ANN technique and location of multiple PD signal based on three-point technique. The multiple PD measurement is modelled and simulated using EMTP-ATP software to obtain the PD signals. These PD signals have been used as a reference for ANN in MATLAB software. In the *nprtool* application in MATLAB, a plot of Receiver Operating Characteristic (ROC) and plot of the confusion matrix have been referred to get the result of classification accuracy. The accuracy of classification with ANN method is compared to the statistical feature extraction to analyze the best accuracy to identify the PD signals. Lastly, the PD signal occurs at the exact location have been classified by using the three-point technique.

3.1 Materials

The 11.5 km long of three phase single line 11 kV XLPE underground power cable for PD signal with three RC sensors placed have been modelled in EMTP-ATP software. The main parts of the configuration are the PD source, RC sensor model and power cables with 240 mm^2 nominal area copper conductor cable. Firstly, PD source based on the single line diagram have been modelled with the network consists of 11 kV source. The amplitude voltage selected was 5 V until 8 V and the signal is created by the fall and the rise times which is labelled as A and B.

Secondly is modelling of line power cable. The single line diagram of line cable used in this project shown as in Figure 1. Based on Figure 1, the circuit started with PD sources with 3 phase monitoring system. It is connected to the single line power cable which separated into 6 locations labelled as L1, L2, L3, L4, L5 and L6 with the length of 2.5 km, 3 km, 1 km, 1.5 km, 1 km and 2.5 km. So, the total length should be 11.5 km long single line power cable for PD signal with three RC sensors. Then, the RC sensor was used in 3 positions to identify the PD signal labelled as RC_A, RC_B and RC_C. It's placed between L1 and L2, between L3 and L4, and between L5 and L6.

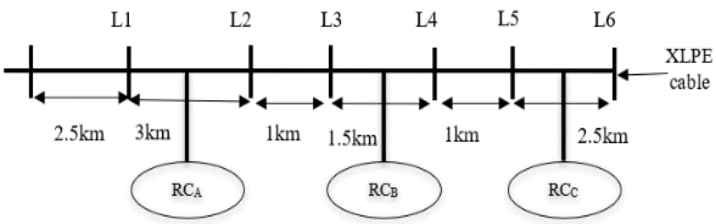

Fig. 1. Single line diagram of line power cable

Lastly, modelling the RC model. The RC sensor was used in three positions to identify the PD signal labelled as RC_A, RC_B and RC_C. A unity transfer function, g(s) = 1/1, was also used to overcome the looping issue for adjusting the value of the TACS controlled current source. It is to prevent the signal from reflect to the cable. Apart from the main part of the configuration, the modelling for the multiple PD measurement of single line 11 kV XLPE underground power cable using EMTP-ATP software can be shown in Figure 2.

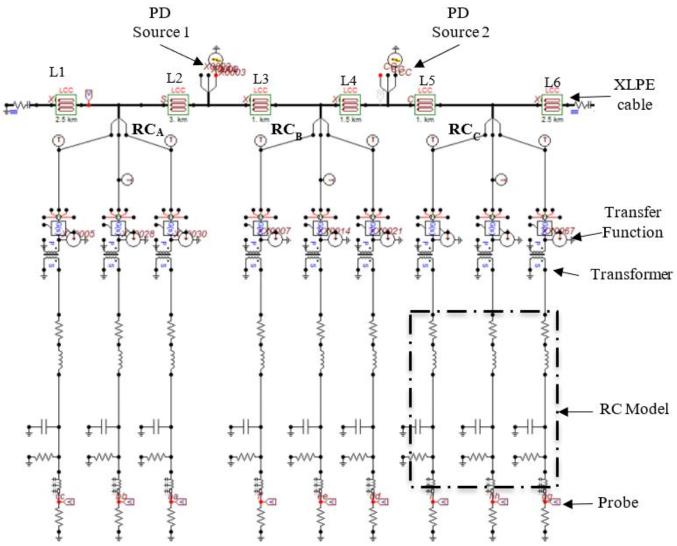

Fig. 2. Modelling the multiple PD measurement of single line 11kV XLPE underground power cable using EMTP-ATP software.

3.2 Samples

The amplitude voltage selected was 5 V until 8 V and the signal is created by the fall and the rise times which is labelled as A and B respectively. This falling and rising time are determined by 10% and 90% respectively from the peak of the signal as shown in Figure 3. Thus, the frequency difference can be considered by the rise and fall times of this PD signal that measured in microseconds.

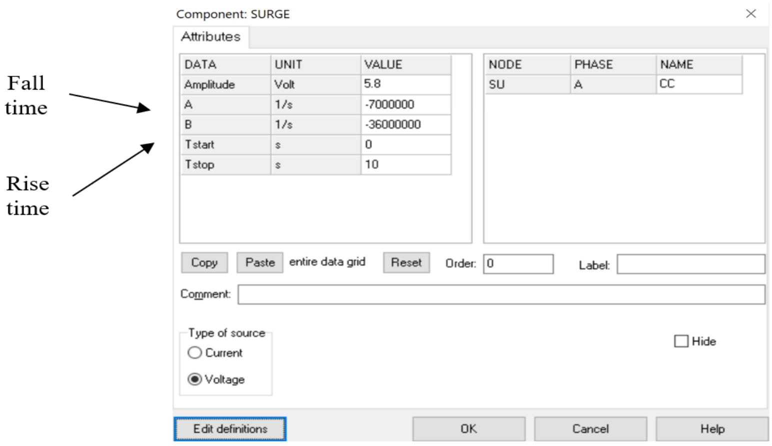

Fig. 3. Single line diagram of line power cable

Figure 3 describes the data used in the software of EMTP-ATP. The data that label as 'A' shows the negative number specifying falling slope while for 'B' as negative number specifying rising slope. However, type of PD had been studied in this project is only internal discharge which range of the rise time used 1 ns until 4 ns as stated in [20]. While for the fall time used is between 60 ns until 70 ns. From the range of the time, the results considered take out for 10 data of the time. Other than that, the amplitude values employed for PD Source in this project are in the range of 5 V to 8 V, resulting in 16 amplitude data. Each amplitude had been used for 10 data of the time. So, the total number of data that may be obtained from the EMTP-ATP software is around 160. Table 4 shows the contribution data for amplitude that had been used as a parameter in EMTP software.

Table 4
Parameter used for amplitude in EMTP-ATP

Data	Amplitude (V)	
	PD Source 1	PD Source 2
1	8.0	5.0
2	7.8	5.2
3	7.6	5.4
4	7.4	5.6
5	7.2	5.8
6	7.0	6.0
7	6.8	6.2
8	6.6	6.4
9	6.4	6.6
10	6.2	6.8
11	6.0	7.0
12	5.8	7.2
13	5.6	7.4
14	5.4	7.6
15	5.2	7.8
16	5.0	8.0

In this data collection, it was obtained the part which used of amplitude 5 V until 8 V. All the data had proceeded as an input of ANN which is to the *nprtool*. For the target it had been taken the data at amplitude 5.8 V. In this project, 16 samples of each PD pattern are used for training. All of these parameters are organised into matrix form as an input matrix and a target matrix. The data had been trained and being compared to the target values that had been set. The things that need to consider in this ANN technique is the confusion and accuracy that achieved 70% and above. So, it can conclude the classification of PD signal had justified. The performance of the training can be seen in the *nprtool* as shown in Figure 4, which have a selection of plotting options of confusion.

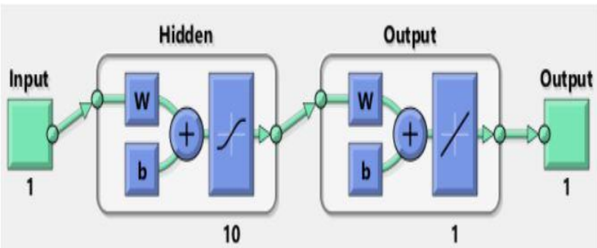

Fig. 4. Neural Pattern Recognition (nprtool) App

There are five main steps to perform ANN: collection data, creating the network, training the model, testing its performance and compare the results in order to analyze the accuracy of PD classification. The data collection is the first step in designing ANN model. As it is outlined, the data had obtained from the results of PD signal in EMTP-ATP software that captured and save in MATLAB format. This data is used as a reference for the PD signal to the ANN technique. In this data collection, it was obtained the part which used of amplitude 5 V until 8 V. All the data had proceeded as an input to the *nprtool*. For the target it had been taken the data at amplitude 5.8 V. The Multi-Layer Perceptron (MLP) model is used by comparing the real data with the estimated output.

The building network had carried out after data collection was obtained in order to train the ANN more effectively. At this stage, the number of hidden layers, neurons in each layer, transfer function in each layer, training function, learning function, and performance function can be specified. Feed forward network is applied to classify the PD signal in this study. A hidden layer in neural network was transform a nonlinear of the inputs entered the network by applies weights to the inputs and directs them through an activation function as the output [22]. Thus, ten hidden layers are used in this project with weights and bias are calculated using sigmoid function.

During the training process, the EMTP-ATP data which have been extracted with statistical features has been selected as input and target as the target data. Validation or testing process has been setup as 30% in *nprtool* as these are used to measure network generalization, and to halt training when generalization stops improving. In this study, 16 samples of each PD pattern are used for training. All of these parameters are organised into matrix form as an input matrix and a target matrix. The data had been trained and being compared to the target values that had been set. The things that need to consider in this ANN technique is the confusion and accuracy that achieved 70% and above. So, it can conclude the classification of PD signal had justified. The performance of the training can be seen in the *nprtool*, which have a selection of plotting options of confusion.

The location of PD signal can be identified by using three-point technique. This technique illustrated based on the equation that need to use which calculate distance between RC sensor that PD signal occurred from sources. The difference of time separated into two conditions which PD that occurred from point RC_A to RC_B called tab while other is PD occurred from point RCB to RCC called t_{cb} that shown in Figure 5.

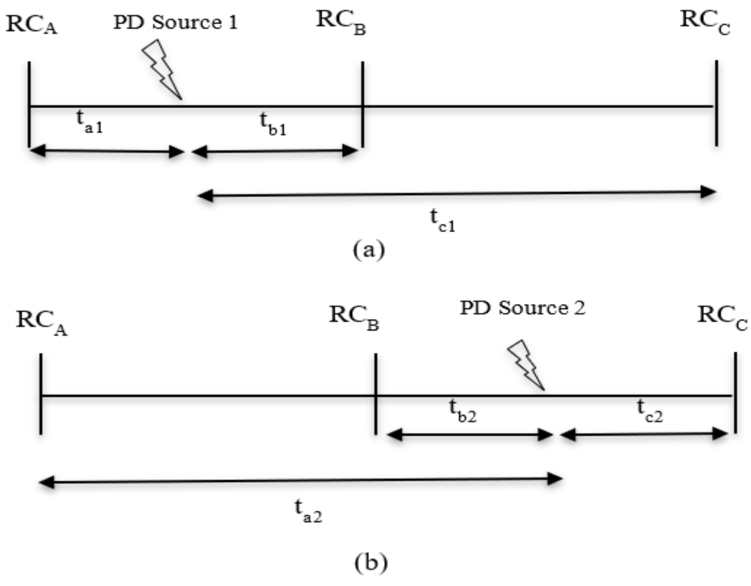

Fig. 5. (a) PD occurred at Source 1 (b) PD occurred at Source 2

The solution for t_{ab} and t_{cb} can be used in Eq. (1) and Eq. (2).

$$t_{ab} = t_{a1} - t_{b1} \tag{1}$$

$$t_{cb} = t_{c2} - t_{b2} \tag{2}$$

From Eq. (1) Eq. (2), the distance of location can be calculated by using Eq. (3) and Eq. (4). It considered from the value of tab and t_{cb} in Case 1 and Case 2.

Case 1: $t_{ab} \leq t_{cb}$

$$X_1 = \frac{1}{4} L \left(\frac{t_{ab}}{t_{cb}} + 1 \right) \quad (3)$$

Case 2: $t_{ab} > t_{cb}$

$$X_2 = \frac{1}{4} L \left(3 - \frac{t_{cb}}{t_{ab}} \right) \quad (4)$$

Thus, the percentages error can get the difference between actual distance and calculated distance based on Eq. (5).

$$\%\, error = \frac{actual\ distance - calculated\ distance}{actual\ distance}\ x\ 100 \quad (5)$$

3.3 Data Analysis

Statistical features extraction is a significant approach used in PD pattern classification to analyze the PD data. It minimizes the scale of the original data and allows for good classification of statistical feature trends for various PD conditions [13]. In pattern recognition, feature extraction is important. The classification algorithm, which is related to PD pulse phase analysis, can be impacted by the accuracy of the extracted features [14]. Skewness, Kurtosis, mean, variance, and standard deviation are some of the statistical factors that were properly considered [29] as in Table 5. The statistical extraction is used in this research to compare with the performance of ANN in term of accuracy of the PD classification.

Table 5
Parameter used for amplitude in EMTP-ATP

Parameters	Function	Equation
Mean	Total impulses over both half cycles averaged.	$\mu = \frac{\sum_{i=1}^{N} x_i}{N}$
Variance	Explains the degree to which a bunch of numbers is dispersed.	$\sigma^2 = \sum_{i=1}^{N} (x_i - \mu)^2$
Kurtosis	Shows how sharp the distribution	$k_\mu = \frac{\sum (x_i - \mu)^3}{\sigma^4}$
Skewness	Displays the distributional symmetry with respect to the normal distribution.	$S_k = \frac{\sum (x_i - \mu)^4}{\sigma^4}$
Standard Deviation	An evaluate of set data value variation	$\sigma = \sqrt{\sum_{i=1}^{N} (x_i - \mu)^2}$

4. Results

4.1 Results from EMTP-ATP Software

The results of the PD signal measurement were obtained from the simulation EMTP-ATP software and classification of PD signal by MATLAB software using ANN technique have been summarized. The

EMTP-ATP software produced a simulation result. Figure 6 shows the PD signal obtained which had captured by the probe.

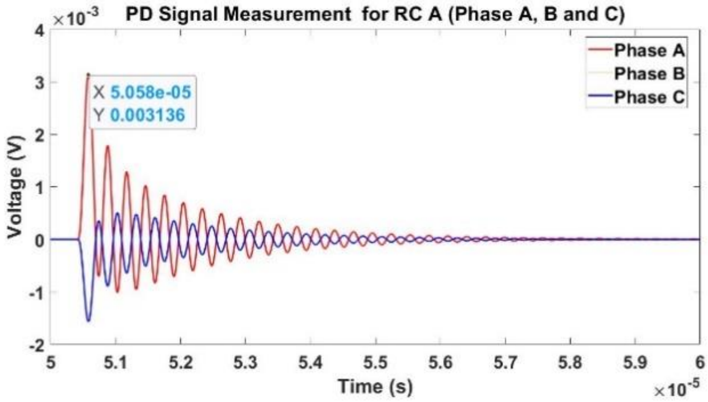

Fig. 6. PD signal measurement for RC A (Phase A, B and C)

According to the results in Figure 6, the PD signal measurement had occurred is at the red-colored signal at Phase A because the signal for the PD must be in a positive signal. Thus, the project can continue with the simulations from Phase A for each RC sensor.

4.2 Results of Classification PD Signal Measurement in MATLAB Using ANN Technique

The usage of *nprtool* in MATLAB software can help with the classification of PD signals, which is particularly useful for identification. Figure 7 shows the result obtained the data with multiple PD signal by considering the plotting of confusion matrix.

Fig. 7. Plot of Confusion Matrix for training, validation, test and overall confusion for Data 1 of RC A at ANN in MATLAB.

The results in Figure 7 can be used to determine the accuracy of neural network training of confusion matrix for training, validation, test and overall confusion. The *nprtool* trains the data using a two-layer feed forward network with slope hidden and output neurons. The input that was trained with the output data is indeed mostly valid. For all confusion matrix, it displays a percent for right data is 70.1 % and a percent for wrong data is 29.9 %. It means that the PD signal measurement is almost get to accurate data. Table 6 shows the result for the Data 1 and 2 based on the percentages of accuracy in confusion.

Table 6
Accuracy for each Range Amplitude and RC Sensor

Data		RC Sensor	Training Confusion (%)	Validation Confusion (%)	Testing Confusion (%)	All Confusion (%)
Data 1		RC A	70.0	71.0	69.4	70.1
Source 1	8.0	RC B	69.5	69.9	68.0	69.4
Source 2	5.0	RC C	70.9	71.5	71.5	71.1
Data 2		RC A	70.7	69.8	69.9	70.5
Source 1	7.8	RC B	65.8	64.7	65.0	65.5
Source 2	5.2	RC C	70.4	71.0	70.4	70.5

4.3 Comparison Results ANN With Statistical Features Extraction

In this section, the result is used by comparing the result with statistical features extraction with the ANN technique. For statistical technique used the five parameters of mean, variance, kurtosis, skewness and standard deviation while ANN method of ANN used the actual data from the EMTP software. all the comparison in term of accuracy in both methods can be shown as in Table 7.

Table 7
Accuracy for ANN and Statistical Features

Data	Pd Source	Parameter	Rc Sensor	Accuracy Confusion (%)	
				ANN	Statistical
Data 1	1	8.0	RC A	70.1	80.0
	2	5.0	RC B	69.4	80.0
			RC C	71.1	80.0
Data 2	1	7.8	RC A	70.5	80.0
	2	5.2	RC B	65.5	80.0
			RC C	70.5	80.0

Table 5 shows the accuracy of the PD signal conduct in ANN and statistical features had been compared. When comparing both, the classification of the PD signal produces very identical results by getting the accuracy of all the results mostly to 80 %. It means all the obtained data had verified the PD signal classification was accurate. By comparing with the time taken for each simulation as shown in Table 8.

Table 8
Comparison the Time Taken for Simulation of ANN with Statistical Technique

Data	Rc Sensor	Time (S)		Difference Percentage (%)
		Ann	Statistical	
Data 1	A	3.00	0.45	85.0
	B	5.00	0.68	86.4
	C	3.00	0.60	80.0
Data 2	A	4.00	0.59	85.3
	B	3.00	0.72	76.0
	C	4.00	0.66	83.5

The result had been computed the comparison time taken for simulation each RC sensor based on the ANN with statistical technique in Table 7. By comparing with the percentage difference between both techniques, almost more than 50 % difference time taken simulated. It can be concluded that the statistical method simulates takes more faster time than using the ANN technique by using the actual value from the EMTP software.

The ANN based categorization training technique begins when the training data has been arranged. Without statistical features, classification takes more time as long as it does with it. Thus, by using statistical technique, it makes easier and faster to simulate the classification and accuracy of data obtained.

4.4 Results from Three-Point Technique

The results of the EMTP-ATP can be utilized in this section to identify the location of the PD signal using the three-point technique. The results of time and voltage for Data 1 and 2 which used the different amplitude at the PD source had been obtained in Table 9. Even though, it only displayed for the Data 1 and Data 2.

Table 9
Result of time and voltage for Data 1 and Data 2

Data	PD Source	Parameter (V)	RC Sensor	Time (us)	Voltage (mV)
Data 1	Source 1	8.0	RC A	30.38	3.408
			RC B	10.22	4.746
			RC C	35.42	3.086
	Source 2	5.0	RC A	55.58	1.099
			RC B	15.25	2.143
			RC C	10.21	2.311
Data 2	Source 1	7.8	RC A	30.38	3.322
			RC B	10.22	4.627
			RC C	35.42	3.009
	Source 2	5.2	RC A	55.58	1.143
			RC B	15.25	2.229
			RC C	10.21	2.403

Table 8 shows the results obtained for the time and voltage at Data 1 and 2. According to the results, when the amplitude of the PD source increases, the voltage for the PD signal increases as well. When the amplitude lowers, the same thing happens. It can be called as a linear proportional. Next, the calculation for the location PD signal at Data 1 was produced in Table 10 by utilizing the Eq. (1) till Eq. (5).

Table 10
Calculation for Location PD Signal for Data 1

	At PD Source 1	At PD Source 2
$\boldsymbol{t_{ab}}$	$t_{ab} = 20.16\ \mu s$	$t_{ab} = 40.33\ \mu s$
$\boldsymbol{t_{cb}}$	$t_{cb} = 25.2\ \mu s$	$t_{cb} = -5.04\ \mu s$
$\boldsymbol{t_{ab} \leq t_{cb}}$ @ $\boldsymbol{t_{ab} > t_{cb}}$	$t_{ab} \leq t_{cb}$	$t_{ab} > t_{cb}$
Location of PD, $\boldsymbol{X_n}$	$X_1 = 2.925\ km$	$X_2 = 5.078\ km$

From the results in Table 9, at PD Source 1, since the value of tab was smaller than t_{cb}, to find the location of PD signal can be used the Eq. (3) for case 1 and get 2.925 km for the length. However, it different for PD Source 2 which used the Eq. (4) because value tab greater than t_{cb}. As a result, the length PD signal occurred at 5.078 km. The percentage error can be calculated by using the Eq. (5) as in Table 11.

Table 11
Calculation for percentage error of PD signal for Data 1

	Distance from RC Sensor	Percentage Error (%)
Location of PD at X_1	RC A	$\% \, error = \frac{1.5\,km - 2.925\,km}{1.5\,km} \, x \, 100$ $= 95\ \%$
	RC B	$\% \, error = \frac{3.5\,km - 2.925\,km}{3.5\,km} \, x \, 100$ $= 16.43\ \%$
	RC C	$\% \, error = \frac{6.5\,km - 2.925\,km}{6.5\,km} \, x \, 100$ $= 55\ \%$
Location of PD at X_2	RC A	$\% \, error = \frac{1.5\,km - 5.078\,km}{1.5\,km} \, x \, 100$ $= 239\ \%$
	RC B	$\% \, error = \frac{3.5\,km - 5.078\,km}{3.5\,km} \, x \, 100$ $= 45\ \%$
	RC C	$\% \, error = \frac{6.5\,km - 5.078\,km}{6.5\,km} \, x \, 100$ $= 21.88\ \%$

According to the results in Table 11, the distance location at PD source 1 was 2.925 km long. When the percentage error had been calculated, it shows the sensor of RC B got the least percent of error at 16.43 %. It means the PD signal for PD source 1 occurred at the RC B sensor which closest to it. While for PD source 2, the calculated distance was 5.078 km. PD signal had occurred at the sensor of RC A because the result recognized 21.88 % as the least percent among the three RC sensors when considering the PD signal using percentage error calculation. However, the location for PD Source 2 at RC A had obtained 239 % which higher for percentage error. It is because due to the conventional method based on the time of arrival. As a result, it may be concluded the PD signal had been used to identify the location at the RC sensor for the detection.

5. Conclusions

In a nutshell, all the results obtained in this project had been successfully carried out based on the objectives stated. In this study, multiple PD signal based on ANN classification technique in terms of accuracy and efficiency had been performed. The feed forward back propagation neural network is the most widely implemented learning ANN in ANN. So, this technique was proven to be accurate in classifying PD signal XLPE power cable. This project also included a statistical features extraction technique developed from PD distributions and used in ANN classification techniques to make the identification process easier. ANN with statistical features contribute to 80% accuracy compared to without statistical. Means that, it helps to minimise the size of the PD signal data and speed up classification processing in order to reduce the computing load and bandwidth.

By using the three-point technique, it can be used for long ranges of underground cable. It necessitates the use of three sensors, which raises the system installation cost. Besides, it necessitates the use of external programming software in testing the circumstance whereby PD happens. Moreover, multiple PD signal based on ANN classification this approach also quite simple and can be used in other high-voltage apparatus including power transformers and power cables.

This project could be useful in providing a basic overview of the concept on PD classification using ANN technique.

In the future, other artificial intelligence techniques can be used to approach the multiple PD signal based on ANN classification. The SVM-based model provided better classification accuracy for the test data corresponding to each type of fault. Besides, locating the sensor close to the PD source can be employed as an improvement method to lower the percentage error for the location of PD signal. Thus, it a quite performed can be apply for the future work of the research.

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