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Partial discharge detection and localization on the medium voltage XLPE cables with multiclass support vector machines

Fatih SERTTAŞ*, **Fatih Onur HOCAOĞLU**
Department of Electrical Engineering, Faculty of Engineering, Afyon Kocatepe University, Afyonkarahisar, Turkey

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Abstract: In medium voltage cables, partial discharges (PD's) are the major problems that trigger electrical insulation failures. Therefore, classification of PD source type and failure localization in medium voltage cables are significant issues of medium voltage engineering. Therefore, in this study, both detection and localization of PD are studied. As a first step, 4 different kind of defects are artificially generated at the same length of the same kind of medium voltage cross-linked polyethylene (XLPE) cables. Consequently, an experimental setup is built. During the experiments, different medium voltage levels are applied to the cables, then the PD signals are measured and recorded. To classify the signals of different defects, different statistics of frequency spectrum of the signals are considered as features. As a final task of this step, multiclass support vector machine is employed and the PD signals are classified. In the second step, one kind of defect is generated at different locations of same kind of longer XLPE cable. Consequently, the cable exposed to different medium voltage levels and PD signals are measured and recorded. The statistics of the data are employed as features. Finally, PD signals measured from different lengths are classified by the help of multiclass support vector machine.

Key words: Partial discharges, pattern classification, fault diagnosis, cross-linked polyethylene insulation, discrete Fourier transforms

1. Introduction

Medium voltage (MV) systems are the high-cost systems that require the highest level of safety. Insulation failures may lead to critical and dangerous accidents that can result in deaths, fires and explosion. These critical reasons make it important to monitor the insulation condition from time to time and to diagnose in early phases. Most of the HV system consists of high-insulated cables and XLPE is one of the most preferred HV cables. Over the past decades, underground cable usage has increased swiftly compared to overhead lines [1]. In the electrical power industry, XLPE cables have an important portion among the HV underground cables. Reliability and durability are the main reasons for this situation [2]. Although there are many advantages of XLPE cables, there are some challenges in making the cable connections such as cable joints. The cable joints are usually accepted as dielectric weakness in consequence of the nature of the insulation discontinuity and the nature of the human made structures. The percentage of insulation failure of the cable joints is 91% and the power cable percentage is 89% [3]. PD detection devices for HV cables vary widely. A novel wireless PD measuring device is presented in [4] to detect partial discharge point of XLPE-insulated cables. In addition to this, inductive sensors are started to use in PD detection [5]. An optimum design of a Rogowski coil that is

*Correspondence: fserttas@aku.edu.tr

able to measure the PD signals from the medium voltage cable is proposed. High frequency current transform (HFCT) and ultra-high frequency (UHF) sensors are widely used in online PD measuring systems [6]. To build an insulation model, artificial PD signal generation and PD signal modelling tools are considered. In [7], a physical model relating PD activity to tree development is proposed. PD emulator simulations are carried out using the CST Microwave Studio software in [8]. Discrete wavelet transform is used effectively for denoising of PD signals [9**?**]. Artificial neural networks [11–14] and fast Fourier transform (FFT) is widely used in PD signal processing [15–19]. Spectrum analyze obtained from the FFT of the PD signal carries significant information especially in the time-resolved PD signals. Classification of the PD signal depends on many parameters. Some of those parameters are noisy/noise-free condition of signal, feature extraction or usage of raw data, using a model of the PD data. Support vector machines (SVM) technique is successful classifier in classification problems. In high voltage partial discharge pattern recognition, detection systems, SVM is utilized especially in recent studies [2, 20]. Considering the literature, nonlinear and multiclass SVM seem to be convenient in classifying PD signals. Differently from past literature, in this study, PD type detection and localization on XLPE-insulated medium voltage cables are both studied. For this aim, an experimental setup is built at the high voltage laboratory of electrical engineering department of Afyon Kocatepe University as mentioned in Section 2. To investigate the type of PD, 4 different type of defects are generated on XLPE cables. On the other hand, to investigate the localization of the PD, same kind of defect is generated on different locations of a cable. All type of cables are exposed to different medium voltage levels (0 to 15 kV). For each cable the PD signals of each medium voltage level are measured and recorded. In this step, the data are measured and recorded as time resolved PD data for 6 times to increase the number of data for classification as detailed in Section 2. After experimental studies, the PD data are preprocessed. In this preprocess phase the data are converted to text data format from the own format of the oscilloscope. Consequently, discrete Fourier transform (as explained in Section 3) is applied to the data. The statistical parameters of the Fourier transforms of the data are considered as features as explained in Section 4. These features are then utilized in the multiclass SVM as training and testing data as mentioned in Section 5. Finally, accuracy of the model is tested with "k-fold" cross validation for all combinations of test and train data. Successes of classification results are presented and discussed in Sections 6 and 7, consequently.

2. Experimental setup

In the high voltage laboratory of Afyon Kocatepe University, partial discharge measurement tests are performed according to the schematic diagram presented in Figure 1. The experiments are carried out in accordance with IEC60270 standard. The experimental environment is covered with Faraday cage. The lengths of the cables are set to 1.5 m. The details of the defects are explained in the Section 2.1.

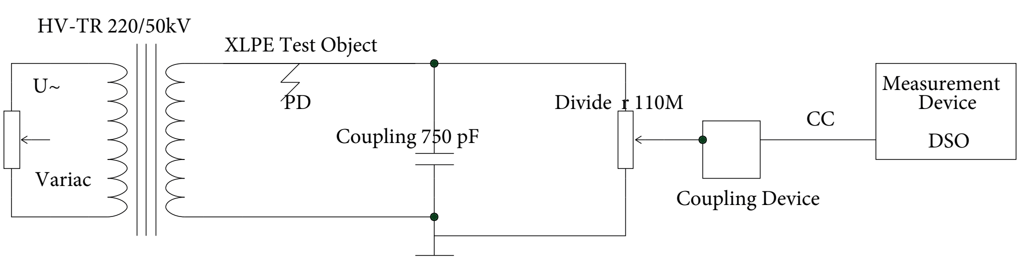

Figure 1. Partial discharge measuring system.

In Figure 1, CK is the abbreviation of coupling capacitor and CA is the capacitive voltage divider. CD express the coupling device and CC is the shielded connecting cable. DSO is the digital signal oscilloscope with

1 GS/s sample rate. The type of PD signals measured and studies were time resolved PD signals since such kind of data carry more information for classification. A typical time based PD signal measured during experiments is illustrated in Figure 2. This signal is collected under 7 kV voltage level whereas PD pulse is occurred at the middle of the measurement. The algorithm for the time-resolved data classification presented in [21] is partially followed in this study.

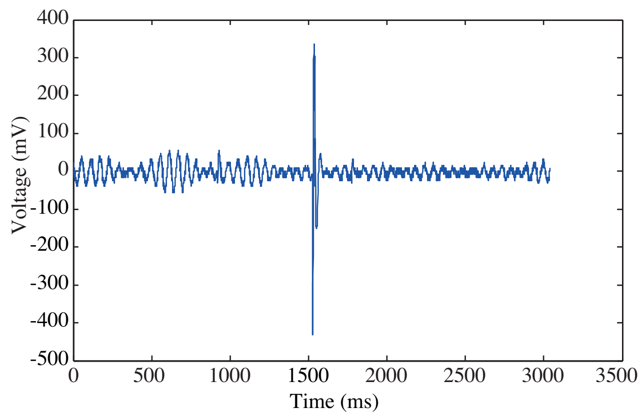

Figure 2. Time based PD pulse signal on a XLPE cable under 7 kV.

2.1. PD detection experiments

Nominal section of $50mm^2 - 36kV$ medium voltage level XLPE insulated HV cables are used in the experiments. Faultless cable is presented in Figure 3. On the other hand, a typical peeled cable that having "close to earth" connection fault is illustrated in Figure 3d. Four different kind of experiments related to PD are performed in the detection part of the study. Artificial defects are considered to have similarities with the real problems in the XLPE cables in use at the electric power systems. Firstly, medium voltage levels are applied on faultless cable and PD activity is observed to assure that there is not any problem with cable insulation. These experiments are also recorded to compare with the PD signals of defects and entitled as "Faultless". As a second experiment, an earth connection is get closer to the cable without any defect on the surface of the XLPE (as seen at Figure 3d). In consequent experiment, a very thin scratch, given in the Figure 3c, is applied on the surface of XLPE cable with an earth connection finally. A needle tip void made with an earth connection on the surface of XLPE cable as presented in Figure 3b.

After the defect forming process on the XLPE and data collecting, frequency spectrum of PD signals are examined and their statistical features are extracted according to the Fourier transformation mentioned in Section 3. Meanwhile, experiments are carried out to perform PD position determination/localization on the same type of XLPE-insulated medium voltage cable.

2.2. PD localization experiments

Electric power systems are complicated and difficult to intervene in case of failure. There are many cables in these complex systems and the length of these cables may be quite long. It is of utmost importance to determine the partial discharges location in the HV cable. It is a critical engineering problem, the power system, installed and operated at highly costs, is recovered at the lowest cost without the occurrence of dangerous failures. In this experimental part of the article, the defect shown in Figure 3b is formed again in the various places of the same

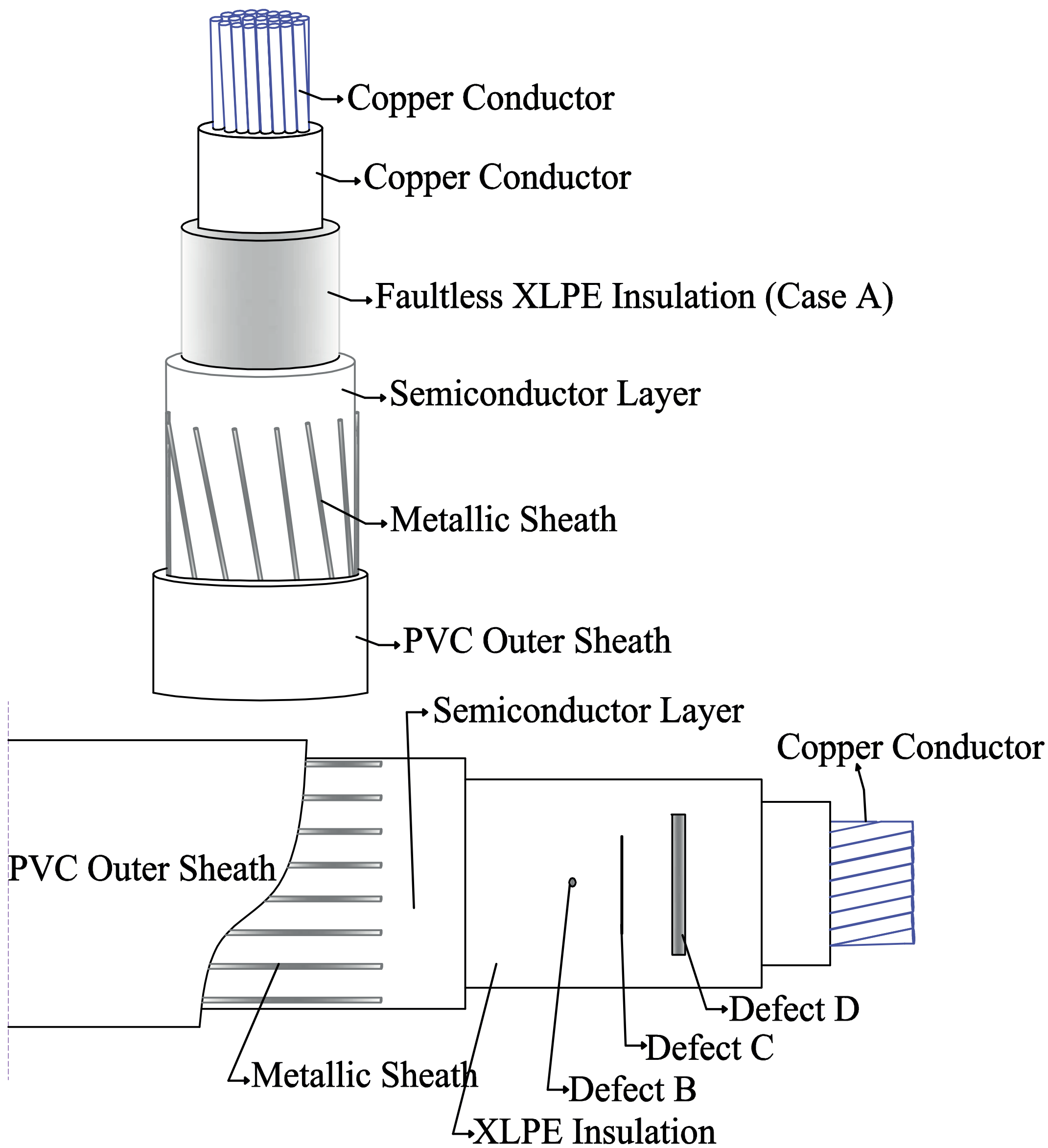

Figure 3. XLPE cable and defects: a) faultless, b) needle tip defect, c) scratch defect, d) close to earth connection.

type of XLPE-insulated medium voltage cable. The PD signals are recorded by measuring for different medium voltage levels. A typical experimental setup built in high voltage laboratory in a Faraday cage is presented in Figure 4. It can be seen from this figure that a high voltage transformer having the maximum voltage level of 50 kV, capacitive voltage divider, coupling capacitor and the XLPE cable are used in the experimental setup.

Various defects are formed on the XLPE insulator part of the medium voltage cable and these defects are defined as the cases of A-B-C-D. In case A, no malfunction has occurred on the cable. Partial discharge measurements are performed by applying high voltages to the nondefected cable. This case has been done in order to compare the measured signals in the event of a malfunction and to distinguish the noise in the measurement, if any. These signals were also needed to detect partial discharge by comparing them with defective state signals. In case B, a needle-sized defect is formed on the XLPE insulator. In the case of C, a capillary scratch defect is effectuated and measurements are made. Finally, in case D, a noncapillary, thicker

Figure 4. PD localization experiments on a XLPE HV cable.

defect is formed and measurements are performed. These defects are preferred as long as there are problems that may occur in the cable while performing the assembly, cable joint and similar operations of the cables.

For the localization process, it is obtained that usage of statistics of the raw PD data as future give better results in these experiments. In these experiments, same type but longer, 7 meter-long XLPE cable is utilized. Locations are defined as line sending, middle point, line end and their distances from the transformer are set to 60 cm, 350 cm, and 640 cm, respectively. Same HV levels are applied to the defected XLPE cables during the experiments.

3. Discrete Fourier transform

While classification, firstly, the raw PD data itself and the statistics of the raw PD data are selected as input features. However in this case considerably low (25%) classification success is obtained. Therefore, it is thought that, usage of the spectral information of the PD data should increase the success of the classification. Hence, information obtained from the discrete fast Fourier transform (FFT) of PD data are considered and used as features.

Discrete Fourier transforms (DFT) are used to convert time-based PD data to frequency spectra with the following FFT equations in (1) and (2).

$$X(k) = \sum_{j=1}^{N} x(j) {\omega_N}^{(J-1)(k-1)} \tag{1}$$

$$\begin{gathered} x(j) = (1/N) \sum_{j=1}^{N} X(k) {\omega_N}^{-(J-1)(k-1)} \\ \omega_N = e^{(-2\pi i)/N} \end{gathered} \tag{2}$$

In (1) and (2), transform and inverse transform are given. N is the vector length and it is 3040 for this study regarding to digital oscilloscope data acquisition limit. FFT is preferred in case of the size of the second or fourth power (exponents) of DFT. In Figure 5, 4 different kinds of spectrums are illustrated for the different defects. It is observed that, high frequency peak values of the spectrum are generally the same in all experiments. Although the laboratory covered with a Faraday cage, these low-amplitude values come from internal noise of oscilloscope and other environmental reasons such as computer, AC control unit etc. However the effect of such noises were ignorable for the experiments.

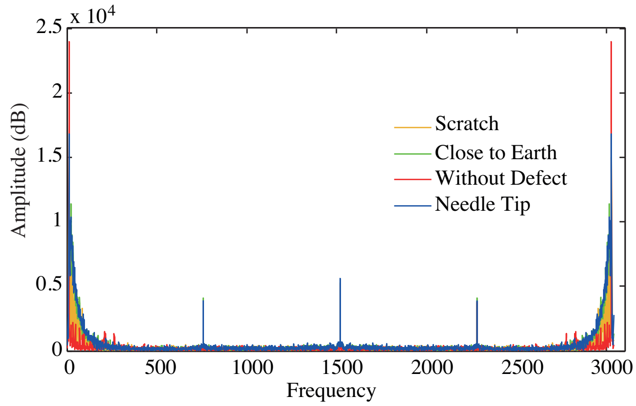

Figure 5. Frequency spectrum of PD signals for different defects.

It is seen from the spectrums that, usage of only the first 300 elements are sufficient since, the difference between the PD's can be clearly observable in that interval. The others mostly represent high frequency noise. The first part of the spectrum analysis is presented in Figure 6, in detail.

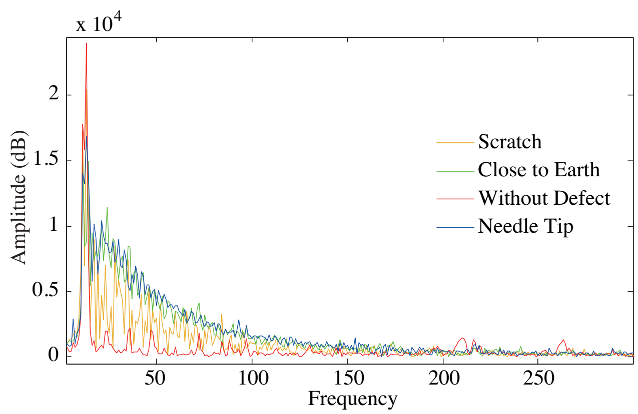

Figure 6. First 300 elements of the frequency spectrum of different PD signals.

It can be observed from Figure 7 that, for "faultless" case (red line in the figures), only very low frequency values appears in the spectrum of the signal. On the other hand as seen, "scratch" differs from others with highly oscillating amplitude. However, PD's of "needle tip" and "close to earth" defects present similar Fourier response in many frequency values that make classification complicate. Therefore, some statistical parameters presented in the following section are considered as features while classification.

4. Statistical feature extraction

Mean value, standard deviation, variance, kurtosis and skewness are considered and used as features for the classification. It should be noted here that these statistics are selected as features due to simulations of classification. While simulations it is obtained that usage of the parameters such as the minimum, maximum and median impair the success of the classification.

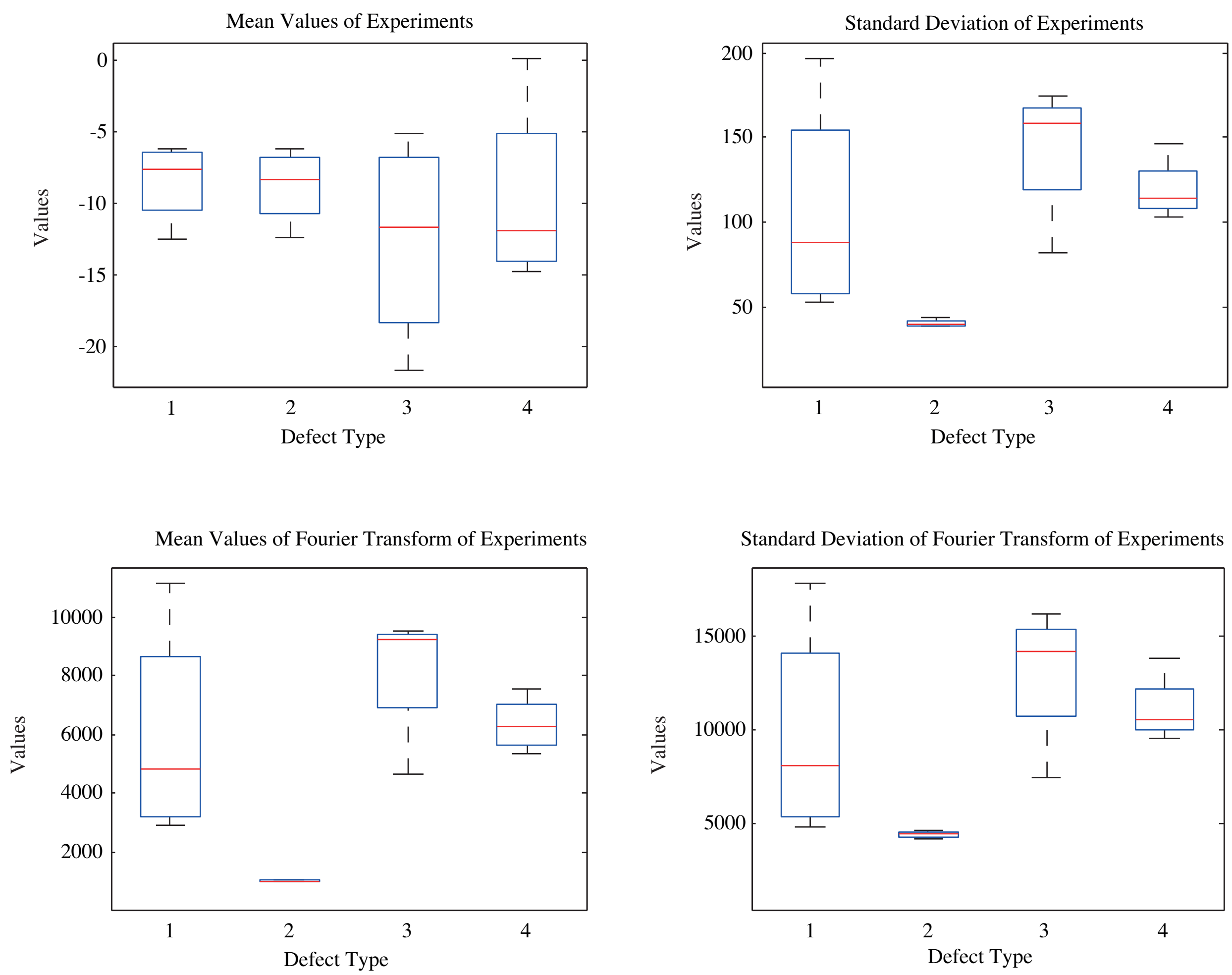

Figure 7. Comparison of mean (above) and standard deviation (below) values of the raw and FFT data.

The statistical parameters of the Fourier transforms of different PD's belonging to different HV levels are presented in Table 1. The formulas for statistical calculations are given in (3),(4),(5),(6),(7), respectively [21].

$$Average\ (mean)\ value\ \ \mu = (X_1 + X_2 + ... + X_n)/n \tag{3}$$

$$Standard\ deviation\ \ \sigma = \sqrt{\frac{\sum_{i=1}^{n}(X_i - \mu)^2}{n}} \tag{4}$$

$$Variance\ \ \sigma^2 = \frac{\sum_{i=1}^{n}(X_i - \mu)^2}{n} \tag{5}$$

$$Kurtosis\ \ = \frac{1}{\sigma^4}\frac{\sum_{i=1}^{n}(X_i - \mu)^4}{n} \tag{6}$$

$$Skewness\ \ = \frac{1}{\sigma^3}\frac{\sum_{i=1}^{n}(X_i - \mu)^3}{n} \tag{7}$$

Table 1. Statistics of Fourier transform of PD signals.

Voltage level (kV)	Needle tip defect				
	Mean (mV)	Std (mV)	Var (mV)	Kurtosis (mV)	Skewness (mV)
3	4,2	20,4	416,7	-0,3	-0,4
5	-1,4	29,9	894,7	4,3	0,4
12	-11,1	156,0	24342,0	70,9	-5,4
15	-11,0	226,1	51140,9	52,7	-5,7
	Capillary scratch defect				
3	3,9	20,9	438,2	-0,5	-0,1
5	3,5	30,1	904,2	0,0	-0,2
12	7,0	150,6	22670,5	122,9	-8,0
15	-10,3	227,2	51625,7	52,6	-5,4
	Close to earth connection defect				
3	5,3	19,7	386,4	-0,7	0,0
5	0,1	31,9	1017,7	2,9	0,4
12	5,6	114,9	13206,5	11,2	-0,8
15	-11,7	189,6	35946,0	14,6	-1,9
	Nondefected Cable				
3	3,9	19,9	395,3	-0,5	-0,3
5	8,4	28,1	789,9	-0,1	-0,5
12	6,1	43,4	1884,6	-0,6	0,0
15	-0,3	45,7	2092,3	-0,7	0,2

In order to understand differences between mean values and standard deviations of the raw PD data statistics and DFT data statistics, box plots are presented in Figure 7. First 2 box plots belong to raw data statistics of PD under 12 kV and the third-fourth box plots belong to Fourier transform of the PD. It can be seen from Figure 7 that the verification of the mean values of FFT is obvious which was not obvious in case the data itself were used.

As the voltage level increases, the statistical characteristics vary according to the defects in the cables. The statistical values at lower voltages are closer to each other as seen from Table 1. Therefore, different voltage levels are considered during experiments.

In faultless case, it is obtained that the kurtosis value is negative for all experiments. According to the finding, if the kurtosis value is positive, the XLPE cable is probably in fault situation. However, it is concluded that it is difficult to understand the type of fault from this value alone. It is also obtained that the increase at voltage level does not cause an increase at statistical values as been at other defect situations.

In Table 2, statistics of the localization measurements are presented for “the line sending point”, “the middle point” and “the line end point” defects. These statistics are for the same voltage value (12 kV). The experiments are repeated 6 times for each distance of defect case to generate more data vector for classification. It is observed that there exist a considerably small amount of difference between the values for 1 type of distance since, monitoring signal of the data in the oscilloscope screen was fluctuating. However, there is not any critical difference that may affect the classification.

Table 2. Statistics of the localization measurements.

	Average (mV)	Std. S. (mV)	Var. (mV)	Kurtosis (mV)	Skewness (mV)
Line sending point	283,0	113,5	12889,4	14,8	-1,1
	283,8	107,7	11591,8	15,6	-0,9
	282,9	110,2	12139,5	24,1	-2,0
	283,9	88,4	7814,4	20,4	-1,0
	283,7	95,1	9047,4	35,1	-2,2
	282,2	116,9	13660,7	24,9	-2,0
Middle point	284,7	75,7	5736,7	36,5	-2,1
	286,9	55,4	3068,1	32,1	-1,5
	284,5	83,3	6940,8	80,2	-4,7
	285,3	68,0	4629,3	28,7	-1,1
	284,4	77,0	5924,7	33,6	-1,5
	284,2	87,1	7592,6	77,8	-4,7
Line end	286,5	37,9	1437,0	53,3	-0,8
	285,9	45,9	2104,1	63,4	-2,3
	286,1	35,0	1221,8	64,6	-1,2
	286,2	46,4	2154,6	35,9	0,2
	285,3	44,5	1981,1	47,2	0,1
	286,0	42,3	1793,5	37,7	0,5

5. Multiclass support vector machines

Support vector machines technique classify 2 classes normally. In this study, there are classes more than 2 and this situation require more complicated technique. In multiclass support vector machines, variables are increased [22]. Learning vectors in 2 classes, and the label vector $y \in R^l$ such that $y_i \in \{1, -1\}$, the SVM method requires the solution of the following optimization problem (8):

$$\begin{array}{ll} \min_{w,b,\xi,\rho} & \frac{1}{2}w^T w - \nu\rho + \frac{1}{l}\sum_{i=1}^{l} \xi_i \\ & y_i(w^T\phi(x_i) + b) \geq \rho - \xi_i, \\ & \xi_i \geq 0, i = 1, \ldots, l, \rho \geq 0. \end{array} \tag{8}$$

In classification we use a voting strategy: each binary classification is considered to be a voting where votes can be cast for all data points x - in the the end point is designated to be in a class with maximum number of votes. Solving multiple problems is more complicated than the binary with the same number of data. The (8) turns into (9) for multiclass SVM method.

We use the “one-against-one” approach in which $k(k-1)/2$ classifiers are constructed and each one trains data from 2 different classes. The first use of this strategy on SVM. For training data from the ith and the jth classes, we solve the following binary classification problem:

$$\begin{array}{ll} \min_{w^{ij},b^{ij},\xi^{ij}} & \frac{1}{2}(w^{ij})^T w^{ij} + C(\sum_t (\xi^{ij})_t) \\ & ((w^{ij})^T\phi(x_t)) + b^{ij}) \geq 1 - \xi_t^{ij}, \text{ if } x_t \text{ in the } i\text{th class,} \\ & ((w^{ij})^T\phi(x_t)) + b^{ij}) \leq -1 + \xi_t^{ij}, \text{ if } x_t \text{ in the } j\text{th class,} \\ & \xi_t^{ij} \geq 0. \end{array} \tag{9}$$

6. Classification and localization results of partial discharges

In this paper, 2 main studies are realized as PD source detection (classification) and localization. Therefore their results are obtained and presented differently. However, the Fourier transform is a common parameter for both experimental studies. Instead of using the entire data set of Fourier transform of any experiment in classification with support vector machines, it is aimed to find the value that has the highest meaning in the classification. Thus, for a measurement experiment, each Fourier transform data is subdivided into subdata (data groups) of 20 elements. The percentages of the effect on success are presented in Table 3. It is observed that some pieces of data have very low effect and some of them had high meanings. This evaluation is utilized to develop the performance of the classification.

Table 3. The effect of the data group of the Fourier to the classification results.

Data group no	Percentage (%)				
1-5	50,0	62,5	58,3	58,3	58,3
6-10	58,3	54,2	50,0	66,7	50,0
11-15	41,7	45,8	62,5	54,2	50,0
16-20	33,3	37,5	41,7	50,0	45,8

Fourier transforms of the partial discharge signals have many elements about the signal. However, some of them have more information about classification. In order to increase the accuracy of the classification, Fourier transform datasets are divided into parts. These parts of Fourier transforms are utilized separately as features in the classification and the results are investigated and compared according to using feature part. It can be seen in the Table 3 that rates are lower than main classification results. Because, in the proposed method, statistical parameters matrix of the Fourier transform dataset is utilized as feature in the classification. However, to test the effect of Fourier parts, Fourier transform data is used as feature directly to speed up operations. For instance, using data group 9 has 66,7% effect whereas 16 has 33,3%. First 10 groups are selected as input signals for feature extraction of classification in terms of high accuracy rates.

6.1. PD source type classification

Multiclass SVM method is performed with statistical features of the Fourier transforms of PD signals from different kind of defects. As the learning data, 5 of the 6 experimental data of a voltage level are utilized. The other feature data is chosen as test data. In Table 4 classification results are given as a k-fold cross validation. It is obvious from the table that considerably accurate classifications are obtained.

Cross-validation is a resampling procedure utilized to evaluate patterns on a limited data sample. The procedure has a single parameter, k, represents the number of groups to divide a particular data sample. When a specific value for k is selected, it can be used instead of k in reference to the model, such as k = 10 cross-validating 10 times. Cross-validation is firstly utilized in applied machine learning to predict the skill of a model on unseen data. It means using a limited sample in order to predict how the model is expected to perform in general when used to make estimations on data not used during the training of the model. Cross-validation method utilized in this paper is illustrated in the Figure 8.

Similar studies have limited input data sample is presented in [26] and [27].In [26], 8 experiments are cross validated. In addition to this, in the [27], 10-fold cross validation is performed.

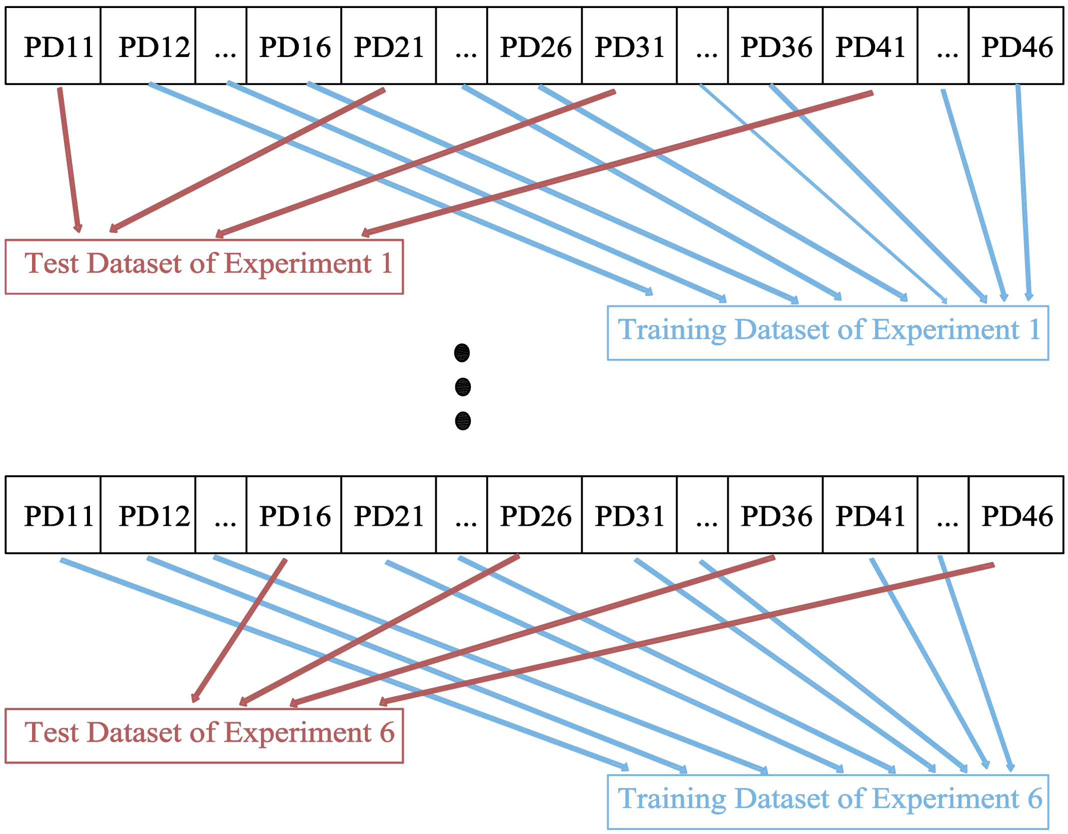

Figure 8. k-fold cross-validation process.

Table 4. Classification validation table.

Test experiment	Desired				Observed				Accuracy
Experiment 1	1	2	3	4	4	2	3	2	50%
Experiment 2	1	2	3	4	1	2	3	1	75%
Experiment 3	1	2	3	4	1	2	3	1	75%
Experiment 4	1	2	3	4	1	2	3	4	100%
Experiment 5	1	2	3	4	1	2	3	1	75%
Experiment 6	1	2	3	4	1	2	3	4	100%
Average									79%

6.2. Localization

Fault localization technics inform the technical person about the position of the failure. For this reason, many recent researches are performed to locate the failure [23, 24]. In this paper, localization process is also carried out with multiclass SVM method. Each location of the defect is defined as classes and these 3 classes are utilized as learning and test data of the method. Localization results are given in Table 5 with k-fold cross validation.

Classification results are presented in Tables 4 and 5. There are 4 classes in Table 4 as there are 4 different types of defects. While the left side of the table shows the class it should be (1-2-3-4), the right side represents the result of the classification algorithm. In Table 5, 3 different positions should be numbered as 1,2 and 3, and should be 1-2-3, while the signal classes resulting from the classification process are presented

Table 5. Classification validation results for each experiments.

Test experiment	Desired			Observed			Accuracy
Experiment 1	1	2	3	1	2	3	100%
Experiment 2	1	2	3	1	2	3	100%
Experiment 3	1	2	3	1	2	3	100%
Experiment 4	1	2	3	1	2	3	100%
Experiment 5	1	2	3	2	2	3	66,6%
Experiment 6	1	2	3	1	2	3	100%
Average							94,43%

respectively. Here, the aim is all partial discharge data, respectively, tested in the classification. Success value was tested by changing combinations of training and test data. This table is defined as the confusion matrix. As an illustration, Figure 8 is added to the article to show the technic.

7. Conclusion

In this article, the statistical features of the Fourier transform of the partial discharge (PD) data are classified by multi-SVM (multiclass support vector machines). XLPE-insulated power cable is preferred because of its widespread use in electrical power systems. As a result of classification, 75% accuracy is achieved firstly with the only statistics of Fourier transform are used. In case of first part of the FFT of the PD's (the lower frequencies of the PD spectrum) are employed, the accuracy of classification reaches approximately 80%. In the second part of the study, fault positioning (localization) is aimed. Statistics of the raw data are employed as features in localization task. In this case, the defects are artificially generated at various locations on the XLPE insulated medium voltage cable. Consequently, experiments are performed and the PD signals are measured from each defected cable during the experiments. Finally statistical parameters of the measured PD data are presented to multiclass support vector machines. Finally, considerably successful (94%) classification accuracy is obtained. This accuracy values are gained by k-fold validation method. The positioning process is also successfully performed with statistical feature extraction and multiclass SVM. The advantages of the proposed method are listed in the following explanations.

- Easily available and uncomplicated features are extracted in this paper. Certain parts of the data set formed by the Fourier transform are preferred (these parts are determined by testing), and are classified into multiclass support vector machines by creating a matrix of their statistical attributes.

- Successful classification results are obtained by combining general statistical methods with different perspectives. In this way, contribution is made to the fault identification and positioning literature.

- Classification is made on the measured signals over the raw data without applying noise filtering such as wavelet transformations which are widely used in the literature. This case is desired in signal processing techniques.

- Determination of the cable defect type causing partial discharge and the localization of the fault on the cable are performed in the same study with similar attributes. In most studies in the literature, these applications constitute the subject of each article.

- The experimental stage is economical as it is carried out in a way that does not require a huge high voltage laboratory and materials of very large physical dimensions. However, the tests are carried out in accordance with the IEC 60270 norms. Since it is planned to be a solution to a real problem, a medium voltage XLPE cable widely used in the electricity market is preferred.

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References

[1] Shafiq M, Kauhaniemi K, Robles G, Hussain GA, Kumpulainen L. Partial discharge signal propagation in medium voltage branched cable feeder. IEEE Electrical Insulation Magazine 2018; 34 (6): 18-29. doi: 10.1109/MEI.2018.8507714

[2] Raymond WJK, Illias HA, Bakar AHA, High noise tolerance feature extraction for partial discharge classification in XLPE cable joints. IEEE Transactions on Dielectrics and Electrical Insulation 2017; 24 (1): 66-74. doi: 10.1109/TDEI.2016.005864

[3] Refaat SS, Shams MA. A review of partial discharge detection, diagnosis techniques in high voltage power cables. In: IEEE 12th International Conference on Compatibility, Power Electronics and Power Engineering; Doha, Qatar; 2018. pp. 1-5.

[4] Madonia A, Sanseverino ER, Romano P, Troia I, Bonon SF et al. Wireless partial discharge tracking on cross-linked polyethylene MV and HV cables. IEEE Electrical Insulation Magazine 2018; 34 (6): 8-17. doi: 10.1109/MEI.2018.8507713

[5] Shafiq M, Kauhaniemi K, Robles G, Isa M, Kumpulainen L. Online condition monitoring of MV cable feeders using Rogowski coil sensors for PD measurements. Electric Power Systems Research 2019; 167: 150-162. doi: 10.1016/j.epsr.2018.10.038

[6] Singsathien J, Suwanasri T, Suwanasri C, Ruankon S, Fuangpian P et al. Partial discharge detection and localization of defected power cable using HFCT and UHF sensors. In: 14th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology; Phuket, Thailand; 2017. pp. 505-508.

[7] Lv Z, Rowland SM, Chen S, Zheng H, Wu K. Modelling of partial discharge characteristics in electrical tree channels: Estimating the PD inception and extinction voltages. IEEE Transactions on Dielectrics and Electrical Insulation 2018; 25 (5): 1999-2010. doi: 10.1109/TDEI.2018.007175

[8] Jaber A, Lazaridis P, Saeed B, Zhang Y, Khan U et al. Validation of partial discharge emulator simulations using free-space radiometric measurements. In: International Conference for Students on Applied Engineering; Newcastle, UK; 2016. pp. 475-478.

[9] Amjad HG, Kumpulainen L, Lehtonen M, Hashmi M, Shafiq M. Signal processing of PD measurements to predict arcing faults in MV switchgears. In: IEEE International Conference on Industrial Technology; Cape Town, South Africa; 2013. pp. 916-921.

[10] Lalitha EM, Satish L. Wavelet analysis for classification of multi-source PD patterns. IEEE Transactions on Dielectrics and Electrical Insulation 2000; 7 (1): 40-47. doi: 10.1109/94.839339

[11] Noel MM, Basappa P, Lakdawala V, Nimbole V. A neural network based system for prediction of partial discharge pulse height distribution parameters. In: IEEE International Symposium on Electrical Insulation; Vancouver, BC, Canada; 2008. pp. 331-335.

[12] Yongpeng X, Yong Q, Xiaoxin C, Aihuiping X, Gehao S et al. Partial discharge feature extraction through contourlet transform for XLPE cable defect models classification. In: International Conference on Condition Monitoring and Diagnosis; Xi'an, China; 2016. pp. 912-915.

[13] Han Y, Song YH. Using improved self-organizing map for partial discharge diagnosis of large turbogenerators. IEEE Transactions on Energy Conversion 2003; 18: 392-399. doi: 10.1109/TEC.2003.815834

[14] Xu Y, Qian Y, Yang F, Li Z, Sheng G et al. DC cable feature extraction based on the PD image in the non-subsampled contourlet transform domain. IEEE Transactions on Dielectrics and Electrical Insulation 2018; 25 (2): 533-540. doi: 10.1109/TDEI.2018.006919

[15] Yusoff NA, Isa M, Hamid H, Adzman MR, Rohani MNKH et al. Denoising technique for partial discharge signal:A comparison performance between artificial neural network, fast fourier transform and discrete wavelet transform. In: IEEE 6th International Conference on Power and Energy; Maleka, Malaysia; 2016. pp. 311-316.

[16] Md Thayoob YH, Ghosh PS, Ghani ABA. Frequency spectral analysis of electrical partial discharge signals in XLPE cable under various soil conditions. In: IEEE 2nd International Power and Energy Conference; Johor Bahru, Malaysia; 2008. pp. 1528-1531.

[17] Md Thayoob YH, Ghani ABA, Ghosh PS. Partial discharge pattern classification using frequency-domain statistical descriptors. In: Electrical Insulation Conference and Electrical Manufacturing and Coil Winding Technology Conference; Indiana, USA; 2003. pp.171-175.

[18] Nainggolan JM, Nakashima T, Sakoda T, Otsubo M, Kurihara S et al. Location of partial discharge at joint section of XLPE cable using acoustic emission technique. In: Conference on Electrical Insulation and Dielectric Phenomena; Indiana, USA; 2010. pp. 1-4.

[19] Li W, Zhao J, Meng S. Partial discharge time-frequency spectrum analysis and extraction for power cable. In: Asia-Pacific Power and Energy Engineering Conference; Shanghai, China; 2012. pp. 1-3.

[20] Sekii Y, Yamauchi K. Analysis of deterioration by partial discharge of XLPE using GCMS and FTIR. In: International Conference on Condition Monitoring and Diagnosis; Beijing, China; 2008. pp. 251-254.

[21] Basharan V, Maria Siluvairaj WI, Ramasamy Velayutham M. Recognition of multiple partial discharge patterns by multi-class support vector machine using fractal image processing technique. IET Science, Measurement & Technology 2018; 12 (8): 1031-1038. doi: 10.1049/iet-smt.2018.5020

[22] Hao L, Lewin PL. Partial discharge source discrimination using a support vector machine. IEEE Transactions on Dielectrics and Electrical Insulation 2010; 17 (1): 189-197. doi: 10.1109/TDEI.2010.5412017

[23] Sahoo NC, Salama MMA, Bartnikas R. Trends in partial discharge pattern classification: a survey. IEEE Transactions on Dielectrics and Electrical Insulation 2005; 12 (2): 248-264. doi: 10.1109/TDEI.2005.1430395

[24] Wang Z, Xue X. Multi-class support vector machine.In: Ma Y, Guo G (editors). Support Vector Machine Applications. USA: Springer International Publishing 2013, pp. 23-48. doi: 10.1007/978-3-319-02300-7-2

[25] Darabad VP. Application of ACF-wavelet feature extraction for classification of some artificial PD models of power transformer. Turkish Journal of Electrical Engineering & Computer Science 2018; 26 (6): 3100-3114. doi:10.3906/elk-1708-17

[26] Ludpa S, Pattanadech N, Leelajindakrairerk M, Yutthagowith P. Pattern classification of partial discharge in high voltage equipment by regression analysis. In: 5th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology; Krabi, Thailand; 2008. pp. 921-924.

[27] Raymond WJK, Illias HA, Abu Bakar AH. Classification of Partial Discharge Measured under Different Levels of Noise Contamination. PLoS One 2017; 12(1): e0170111. doi: 10.1371/journal.pone.0170111