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Performance Evaluation of AI-based Algorithms for Condition Assessment of Power Components

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Abstract –**This study compares the performance of different artificial intelligence (AI) based algorithms/ classifiers used for partial discharge (PD) classification during insulation diagnostics in power components. During PD measurements, a considerable amount of data is collected, and processing such a huge amount of data is time-consuming and expensive. The useful PD signals can be extracted from the measurements, and AI-based algorithms can be used to process those signals for classification and diagnostics purposes. In this work, the data is collected from three different PD sources, namely, corona, internal, and surface in the high voltage laboratory. Each measurement consists of the PD activity captured in the form of power frequency cycles. The single PD pulses are extracted from the measured signals using the segmentation method. For features extraction, at first discrete wavelet transform (DWT) technique is applied on single pulses, and then statistical parameters (mean, standard deviation, skewness, and kurtosis) are applied to the extracted features. To classify different PD sources, two different classifiers, support vector machine (SVM) and k-nearest neighbors (KNN) with their types, are applied to extracted features. The performance of each classifier is evaluated using the accuracy performance indicator by varying the amount of input PD data from each PD source. The developed understanding will enable researchers/asset managers to extract the required amount of data from the field measurements.**

Keywords: Partial Discharge, Condition Monitoring, Artificial Intelligence, Machine Learning, Performance Evaluation

I. INTRODUCTION

Partial discharge (PD) occurs due to insulation degradation, and PD measurement is an essential technique to diagnose the electrical insulation in power components. PD monitoring indicates incipient faults/early generating faults, especially for those components in which PD is not observed in regular operation. The PD faults/incipient faults in power components can be classified as corona PDs, surface PDs, and internal PDs [1], [2]. Corona PD is not considered a critical issue compared to surface PD and internal PD because corona PD does not directly degrade the insulation of power components. Surface and internal PDs considerably impact the insulation of power components. Because energetic particles in the discharge process directly interact with the insulation, that results in insulation degradation and eventually leads to power component breakdown [1].

In power systems, the accuracy of diagnosis of power components determines the reliability and efficiency of the power network. Condition monitoring is essential to estimate power components' state and avoid unplanned outages/maintenance. Automated tools are gradually replacing human involvement in deciding the actual fault conditions. Emerging technologies such as Artificial Intelligence (AI) are being used as advanced tools to automate the condition monitoring process for detecting incipient faults at an early stage. Similarly, Machine Learning (ML) algorithms are becoming an increased interest for researchers to avoid unintentional failures in the power network. For researchers or algorithm developers, selecting ML algorithms is critical because it mostly depends on the input data. In addition, the accuracy of results has been deemed carefully during the processing of features extracted from the huge data [3].

Researchers have made many successful attempts by utilizing AI and ML algorithms to classify PD defects, and their contributions are published as research papers. Many machine learning algorithms are used in the literature for PD classification, such as; decision tree (DT), Support Vector Machine (SVM), k-nearest neighbors (KNN) and Artificial Neural Networks (ANN). Researchers in [4] tested the 11 kV XPLE cable for the classification of PD faults using ANN and SVM. In [5], the authors compared the classification results of SVM, KNN, DT and Back Propagation Neural Network (BPNN) methods on a similar cable type. Good enough results were also achieved by the KNN method and for some features by DT. The SVM was also used in [6] and [7] to classify defects in the power switchgear and transformer insulation.

The questions such as; what amount of data, the features used by the classifiers, and which algorithm or classifier has better performance are important to consider when applying AI-based solutions. The answers to the above questions are not straightforward and need many experiments and data analysis tasks. Our previous studies [2], [8] have found suitable features and classifiers. This study investigates the performance of classifiers by varying the total amount of data and data sets of each PD defect by keeping the same features and classifiers used in previous work [2], [8]. Identifying PD types is needed to carry out the maintenance strategy of observed components for repairing or replacing. For identification, AI /ML algorithms have been widely used for PD classification. The two standard algorithms/classifiers used for PD classification are SVM and KNN [8].

This research paper aims to evaluate the performance of AI-based methods for classifying PD data from different sources. We will use two classification algorithms: SVM and KNN, with their types. The SVM and KNN classifiers with their six types will be used for different case studies to classify PD data sets for different PD defects and identify the best-performing classifier based on accuracy.

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The structure of this paper is as follows: Section II describes the Experimental Setup for PD defects preparation and measurement, and section III explains the methodology for the diagnosis process (data collection, data preprocessing, features extraction and data classification). The results and discussion are presented in section IV, and the conclusion is provided in section V.

II. EXPERIMENTAL SETUP

In this paper, the classification of three types of PD sources (corona, surface and internal) is carried out. The measurements were taken from the experiments that were made at the High Voltage Laboratory of the University of Vaasa, Finland. In this experimental setup, two separate cables with a nominal insulation thickness of 5.5 mm and a length of 3.3 meters were used to measure internal and surface PDs. For the corona PD source, a pin-plate electrode was used where a pin with a sharp edge is kept at a distance of a few millimeters (mm) from the plate. Surface discharges were produced by disconnecting the stress cone at one end of the first cable. The internal discharges were created by a deep cut on the cable's outer jacket down to the insulation of the second cable[9]. These PD sources are shown in Fig. 1.

The experimental setup layout is depicted in Fig 2. The setup was developed according to the requirements of the IEC 60270 standard for PD measurements. For PD measurements from this experimental setup, a high voltage coupling capacitor of voltage rating 100 kV and capacitance one nF was connected with a high-frequency current transformer (HFCT). The HFCT had a transfer ratio of 1:10 and a bandwidth of 80 MHz (-3dB). A high-frequency digital storage oscilloscope was connected with the HFCT via a coaxial cable, and PD data were measured at a sampling frequency of 250 mega samples per second (MS/s).

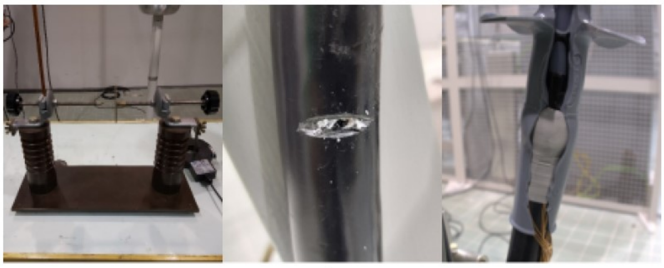
(a) (b) (c)

Figure 1. PD sources (a) corona (b) surface (c) internal

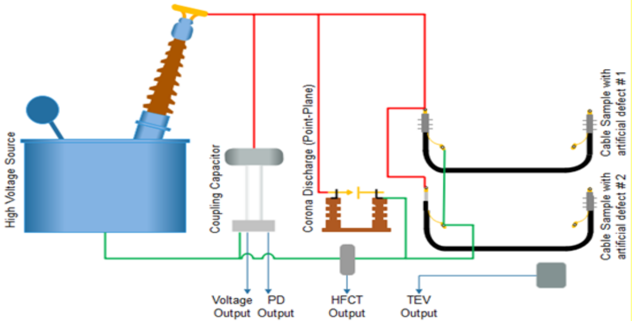

Figure 2. Measurement Setup

The PD sources were energized for each case (corona, internal and surface) using a high voltage power transformer, and the voltage was increased up to the PD inception voltage (PDIV) level. The measurement was carried out at an applied voltage greater than the PDIV, and measured data was stored in computers for analysis and classification purposes [9].

III. METHODOLOGY

Data-driven faults diagnosis process is widely used for condition monitoring of power components. This process is divided into four steps: data collection, data preprocessing, feature extraction, and fault classification [10].

A. Data Collection

In order to measure the PD activity for each PD defect, the voltage level from the variable power supply was increased up to the stage when PD activity started. The PD inception voltage (PDIV) for corona, surface, and the internal defect was measured as 11.6 kV, 5.9 kV, and 5.4 kV respectively. The applied voltage was increased in order to get a suitable amount of PDs. The oscilloscope has the measurement capability of capturing 32 measurements at consecutive time instants. For this study, the data was measured at 15.3 kV for corona, 13.3 kV for surface, and 12. 8 kV for internal discharges.

B. Data Preprocessing

Data preprocessing of huge and different sources of data is a time-consuming and challenging task. The preprocessing method and running time depend on the nature of the data that is considered. The data of three types of PD defects were loaded into MATLAB software for preprocessing of PD data. At first, the data of the corona PD source was loaded and divided into 75 segments. The segmentation process (splitting of data into chunks) is used here to make the data preprocessing process easier for the extraction of PD pulses. The peak command extracted PD pulses by assigning the threshold value of 0.015. This threshold value is selected to remove the noise from pulses or extract noise-free pulses. The selection of threshold is made after visualizing the original signal. The upper and lower bounds for peak selection are defined to extract the PD pulses with a width of 1000 samples/data points (starting from 50 samples before the peak value). This width is kept constant for extracting PD pulses from all three PD defects. The process/method for extracting PD pulses from other PD sources (Internal and Surface) is the same except for the number of segments. For Surface PD, 70 segments are selected for extracting PD pulses. Whereas, for internal PDs, 20 segments were applied. The number of segments is selected based on pulses' density and the distance between pulses.

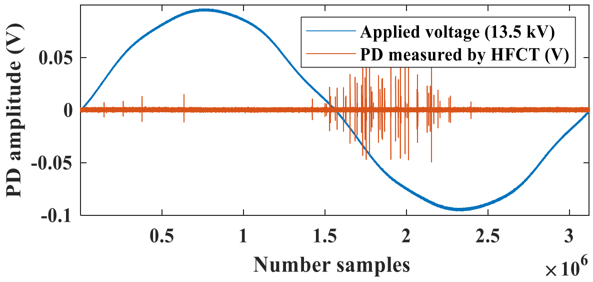

Figure 3. Surface PD signal

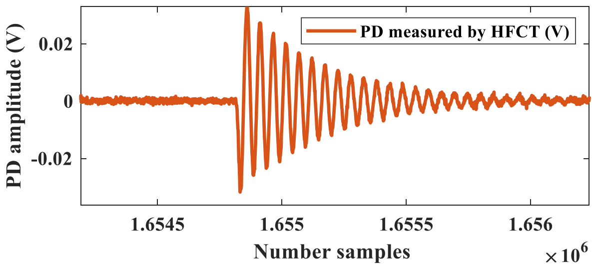

Figure 4. A PD pulse extracted from Surface PD activity

The original signal with the number of PD pulses for surface PD defect is shown in Fig. 3, consisting of 3125000 samples (captured with a sampling period of 6.4 ns) for one cycle of 20 ms. In contrast, one extracted PD pulse consists of 1000 samples, as shown in Fig. 4. The extracted PD pulses are stored as a separate variable for further processing.

The total number of extracted pulses from a single file/measurement of the corona PD source is 21, while the extracted pulses from the surface and internal PD sources are 17 and 6. For the data classification task, several internal PD measurements are required to keep the number of pulses close to the pulses of corona PD defect for better classification.

C. *Features Extraction*

A common data classification approach is extracting the useful features and using them as input for classifiers/ML algorithms. The dominant features can be extracted using time domain and frequency domain analysis, which can be utilized as an input for classifiers. Our previous studies[11], [12] have indicated that wavelet-based features using the discrete wavelet transform (DWT) technique provide promising results for PD classification. The DWT symlet type 7 technique is used in this study to extract the useful features. The DWT first takes PD pulses as an input signal and uses its high pass and low pass filters to extract the features until level 4. At level 4, we have five extracted features using DWT. Statistical-based features, namely; mean, standard deviation, skewness, and kurtosis parameters, are also used in the literature [13] for feature extraction from PD signals. In this study, we have used these four statistical parameters on the extracted DWT-based features that have given us 20 features in total that we have used for PD classification.

D. *Data Classification*

Commonly used classifiers, support vector machines (SVM) and k-nearest neighbors (kNN) are used for the data classification of PD defects/faults.

SVM classifier belongs to the supervised learning machines group, which can handle complex classification problems. SVM is a statistical learning tool that creates separating planes for each data class. This learning algorithm can be used to classify non-linear PD data using a non-linear mapping function in addition to linear PD data. The principle of SVM is finding a decision boundary, separating the space into two halves. Usually, it needs just a few support vectors, the closest ones to the decision boundary [4], [14].

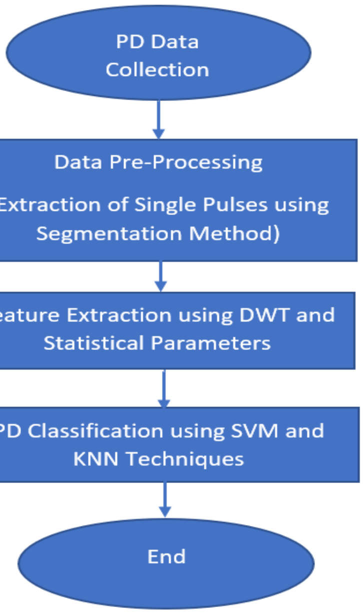

Figure 5. Flow chart of classification algorithm

The KNN algorithm uses distance matric to find the k closest samples and assigns the new sample to the most frequent one of those k samples. The difficult task when using the KNN algorithm is determining the correct number for k [5],[15].

The data-driven faults diagnosis process for classification of PD defects is shown in Fig. 5, and the procedure for PD classification is are summarized as follows:

- The PD data of three types of sources have been collected.
- The source data have been segmented to get useful PD pulses.
- Signal Processing based features have been extracted using the DWT technique from source data, and statistical parameters are used for further extraction of features, as explained in Section 3.3.
- The extracted features are provided as input to classifiers (SVM and KNN) with their types for PD classification.

IV. RESULTS AND DISCUSSION

The two ML classifiers were trained using k-fold cross-validation (CV). K-fold cross-validation is a well-known technique that is used to protect the models against under and overfitting. In this work, a 5-fold CV is chosen. The K-fold cross-validation technique involves splitting data into k-subsets/k folds that are chosen randomly. The model is trained on k-l folds and validated with the remaining fold. The training data are the observations that are not used in the validation data set. The final evaluation is the average of all k folds [16].

The performance evaluation of the trained machine learning classifiers is usually measured by accuracy. Accuracy can be defined as the ratio of a number of correct predictions to the total number of predictions. Moreover, for binary classification, accuracy can be calculated in connection with positives and negatives values as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

TP and TN are True Positives and True Negatives, while FP and FN are False Positives and False Negatives [4].

Nine case studies are investigated in this research paper to identify the best classifiers for the different number of data sets of each PD defect and to develop the understanding for better extraction of the amount of the data from the field measurements. Our approach for each case study is to use the number of PD pulses of different defects as close as possible to the pulses of corona PD defect. In total, thirty-two measurements of internal PD defect are utilized in our case studies, and thirty-two measurements of internal PD defect are used for case study 9. The number of pulses from each PD defect and the number of measurements of each PD defect for nine case studies are shown Table I.

TABLE I. CASE STUDIES FOR DIFFERENT NUMBER OF MEASUREMENTS OF PD DEFECTS

Case Type	**Number of Measurements**			**Number of Extracted Pulses**		
	Corona	***Surface***	***Internal***	***Corona***	***Surface***	***Internal***
1	1	1	3	21	17	18
2	2	2	7	42	34	42
3	3	4	11	63	68	66
4	4	5	14	84	85	84
5	5	6	17	105	102	102
6	6	7	21	126	119	126
7	7	8	24	147	136	144
8	8	10	28	168	170	168
9	9	11	32	189	187	192

It can be seen from Table 1 that a more significant number of measurements are required from the internal PD source for classification purposes. For case study 9, nine measurements are taken from corona PD source and eleven measurements from surface PD source, while thirty-two measurements are taken from internal PD source. These case studies indicate that a researcher needs to collect a huge amount of data from internal PD sources compared to corona and surface PD sources for PD classification. The results for case studies are shown in Table II-Table X.

TABLE II. RESULTS FOR CASE STUDY 1

Case Type	**Classifier**	**Classifier Type**	**Accuracy**
1	SVM	Linear	94.6%
		Quadratic	100.0%
		Cubic	100.0%
		Fine Gaussian	94.6%
		Medium Gaussian	96.4%
		Coarse Gaussian	89.3%
	KNN	Fine	98.2%
		Medium	85.7%
		Coarse	37.5%
		Cosine	85.7%
		Cubic	80.4%
		Weighted	98.2%

TABLE III. RESULTS FOR CASE STUDY 2

Case Type	**Classifier**	**Classifier Type**	**Accuracy**
2	SVM	Linear	100.0%
		Quadratic	100.0%
		Cubic	100.0%
		Fine Gaussian	100.0%
		Medium Gaussian	100.0%
		Coarse Gaussian	93.2%
	KNN	Fine	98.3%
		Medium	89.0%
		Coarse	34.7%
		Cosine	89.0%
		Cubic	89.0%
		Weighted	96.6%

TABLE IV. RESULTS FOR CASE STUDY 3

Case Type	**Classifier**	**Classifier Type**	**Accuracy**
3	SVM	Linear	100.0%
		Quadratic	100.0%
		Cubic	100.0%
		Fine Gaussian	100.0%
		Medium Gaussian	100.0%
		Coarse Gaussian	90.4%
	KNN	Fine	100.0%
		Medium	95.9%
		Coarse	55.8%
		Cosine	96.4%
		Cubic	96.4%
		Weighted	100.0%

SVM gives 100% accuracy with all its types except for Coarse Gaussian SVM, which gives still more than 90% accuracy for cases 2 - 7, while 100% accuracy is achieved with all types of SVM for cases 8 and 9. From the results of the SVM classifier, the understanding can be developed that the number of PD pulses should be at least 118 pulses (seven measurements of internal=42 pulses, two measurements of surface=34 pulses and two measurements of corona=42 pulses) for better PD classification.

TABLE V. RESULTS FOR CASE STUDY 4

Case Type	**Classifier**	**Classifier Type**	**Accuracy**
4	SVM	Linear	100.0%
		Quadratic	100.0%
		Cubic	100.0%
		Fine Gaussian	100.0%
		Medium Gaussian	100.0%
		Coarse Gaussian	94.5%
	KNN	Fine	100.0%
		Medium	96.4%
		Coarse	66.4%
		Cosine	96.8%
		Cubic	97.2%
		Weighted	100.0%

TABLE VI. Results for case study 5

Case Type	Classifier	Classifier Type	Accuracy
5	SVM	Linear	100.0%
		Quadratic	100.0%
		Cubic	100.0%
		Fine Gaussian	100.0%
		Medium Gaussian	100.0%
		Coarse Gaussian	94.5%
	KNN	Fine	100.0%
		Medium	97.1%
		Coarse	70.6%
		Cosine	97.1%
		Cubic	97.4%
		Weighted	100.0%

TABLE VII. Results for case study 6

Case Type	Classifier	Classifier Type	Accuracy
6	SVM	Linear	100.0%
		Quadratic	100.0%
		Cubic	100.0%
		Fine Gaussian	100.0%
		Medium Gaussian	100.0%
		Coarse Gaussian	94.3%
	KNN	Fine	100.0%
		Medium	98.1%
		Coarse	71.7%
		Cosine	98.1%
		Cubic	98.9%
		Weighted	100.0%

TABLE VIII. Results for case study 7

Case Type	Classifier	Classifier Type	Accuracy
7	SVM	Linear	100.0%
		Quadratic	100.0%
		Cubic	100.0%
		Fine Gaussian	100.0%
		Medium Gaussian	100.0%
		Coarse Gaussian	98.4%
	KNN	Fine	100.0%
		Medium	97.9%
		Coarse	70.5%
		Cosine	98.6%
		Cubic	97.9%
		Weighted	100.0%

The classification accuracy for Fine KNN and Weighted KNN is 100% for cases 3-7. The classification accuracy for Medium, Cosine and Cubic KNN is between 80% - 97% for cases 1-7.

TABLE IX. Results for case study 8

Case Type	Classifier	Classifier Type	Accuracy
8	SVM	Linear	100.0%
		Quadratic	100.0%
		Cubic	100.0%
		Fine Gaussian	100.0%
		Medium Gaussian	100.0%
		Coarse Gaussian	100.0%
	KNN	Fine	100.0%
		Medium	100.0%
		Coarse	72.3%
		Cosine	100.0%
		Cubic	100.0%
		Weighted	100.0%

TABLE X. Results for case study 9

Case Type	Classifier	Classifier Type	Accuracy
9	SVM	Linear	100.0%
		Quadratic	100.0%
		Cubic	100.0%
		Fine Gaussian	100.0%
		Medium Gaussian	100.0%
		Coarse Gaussian	100.0%
	KNN	Fine	100.0%
		Medium	100.0%
		Coarse	79.8%
		Cosine	100.0%
		Cubic	100.0%
		Weighted	100.0%

The classification accuracy for both classifiers with their types (SVM and KNN) is 100% for cases 8 and 9 except for Coarse KNN (accuracy 72.3% for case 8 and accuracy 79.8% for case 9). Both classifiers have achieved very good classification results for a large amount of data (506 PD pulses for case 8 and 568 PD pulses for case 9).

V. Conclusion

In this work, the classification performance of AI algorithms is studied based on the amount of data and extracted pulses of the voltage signal from PD sources. PD classification is performed using AI-based algorithms: SVM and KNN with their types. PD data was collected from three different PD sources (corona, surface, and internal discharges) using artificial PD defects as test objects. The features were extracted from the PD pulses (preprocessed data) using DWT as input to the classifiers (SVM and KNN). The classification results of case study 8 and case study 9 demonstrated improved performance compared to case studies 1-7 using SVM and KNN algorithms. Case study 2 showed the minimum limit for the number of measurements for better PD sources classification. The presented work aims to develop an understanding of extracting the required amount of data from the field measurements for efficient classification of PD sources in terms of accuracy, data processing capabilities, time, and associated costs.

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