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Comparison of Machine Learning Algorithms for Classification of Partial Discharge Signals in Medium Voltage Components

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***Abstract*— Partial discharge (PD) diagnosis is an effective tool to track the condition of electrical insulation in the medium voltage (MV) power components. Machine Learning Algorithms (MLAs) promote automated diagnosis solutions for large scale and reliable maintenance strategy. This paper aims to investigate the performance of two MLAs: Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) for the classification of different types of PD sources. Suitable features are extracted by applying statistical parameters on the coefficients of discrete wavelet transform (DWT) for observing the performance of both MLAs. The performance of the algorithms is evaluated using key performance indicators (KPIs); accuracy, prediction speed and training time. Besides KPIs, a confusion matrix is presented to highlight the accurately classified and misclassified PD signals for the SVM algorithm. Comparative study of both algorithms demonstrates that SVM provides better results as compared to the KNN algorithm. The proposed solution can be valuable for the development of automated classification.**

Keywords*— *electrical insulation, partial discharge, features extraction, machine learning algorithms, classification, key performance indicators

I. INTRODUCTION

Electrical insulation is one of the most common causes of electrical breakdown in power components, especially during medium and high voltage operations. Insulation degradation results in electrical discharges which emerge due to localized breakdown within the deteriorated portion of the insulation. These localized discharges are called partial discharges (PDs), which further stimulate the degradation process and finally lead to a complete breakdown of the affected components. PD monitoring is considered an effective tool to track the power components' insulation condition proactively and hence provide an opportunity to determine the maintenance strategy for replacing, repairing, or stand by the component.

PDs in power components are of different types, such as; corona, surface, and internal discharge [1]. Not all the PD types pose a critical threat to the components. Therefore, it is significantly essential to recognize and classify the types of the measured PDs. Accurate recognition of the PD type can enable the condition monitoring specialists and asset managers to execute a best-needed response. Based on the characteristics study and long-term experience, experts perform PD type diagnosis with a certain level of accuracy. Such manual recognition is, however, not only time-consuming and expensive but also vulnerable to diagnosis ambiguity when more than one type of PD source are active simultaneously. While the MV grid is growing and the number of components is increasing, the magnitude of the problem is elevating [2]. Therefore, development of the efficient and automated PD classification solutions is decisive for large scale and reliable diagnosis in the power network.

The conventional approach of PD source recognition is carried out by time-domain analysis to observe the presence of the PD activity during positive and negative half-power cycles. Phasor location, pulse repetition behaviour, and the ratio of the amplitude of the PD signals are well-known PD characteristics in this case [3]. This task is considerably convenient when a single PD type is active.

When multiple PD sources are involved, human expertise is not sufficient to accomplish the discrimination task, especially when the PD activity has reached an aggressive level.

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Stepping forward is enabled by modern data processing techniques, towards which a great interest has been observed during recent years [4]. Feature extraction has emerged as a valuable tool for PD classification. Feature extraction is done based on the PD variables or PD characteristics such as pulse amplitude, pulse width, repetition rate, and rise time. These PD variables are directly related to the physical and operational dynamics of the insulation defect source [1]. Due to the inherent randomness of the PD mechanism, feature extraction based on fewer variables provide an unreliable classification. Therefore, the use of more variables with recognizable trends can give greater accuracy. This paper presents a simple feature extraction technique that provides good classification results for the PD signals. This technique is based on wavelet transform in which statistical parameters are derived from discrete wavelet transform (DWT). The technique is applied to the PD signals to use it as an input for machine learning algorithms (MLAs).

There are many MLAs, such as; artificial neural networks, deep learning, fuzzy logic-based classifier, rough set theory, inductive inference algorithm, support vector machine (SVM) and k-nearest neighbors (KNN), that are used for PD classification in literature [5]-[6]. In this paper, two MLAs: SVM and KNN, with their different types, are utilized on given input features to see their performance using different key performance indicators (KPIs).

The paper is organized as follows: Section II describes the experimental setup for measuring PD signals. Section III presents the PD classification methodology (features extraction, classification algorithms, training data). Moreover, the evaluation parameters (KPIs) are illustrated in this section. The results are discussed in section IV, and Section V concludes this paper.

II. EXPERIMENTAL ARRANGEMENT

The experimental study is done in a high voltage laboratory environment. Above mentioned three types of PD sources (shown in Fig.1) were used once at a time to collect the PD data for PD recognition using the proposed algorithm. The experimental setup was based on the IEC60270 Standard for PD measurements. Depicting the presence of the PD inside the real power components, the PD sources were connected to the MV 20 kV switchgear.

The detailed experimental setup is shown in Fig. 2. The power was supplied by a variable power supply in order to adjust the voltage level above the partial discharge inception voltage (PDIV) for each PD source. The measurements were done considering single-phase operation and thus energizing one line of the switchgear. The PD sources are shown as corona discharge source- CDS, surface discharge source- SDS, and internal discharge source- IDS.

(a) (b) (c)

Fig. 1. Three Types of PD sources: (a) Corona at the needle, (b) PD in the void, (c) Surface PD [7]

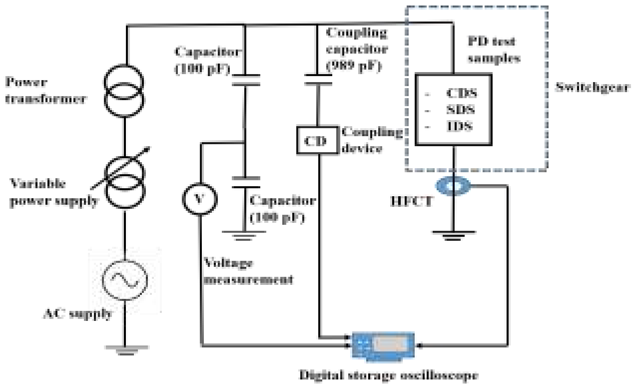


Fig. 2. Detailed Experimental Setup

The metallic body of the switchgear was grounded. A high-frequency current transformer (HFCT) was installed around the ground connections to measure the PDs developing inside the switchgear. The HFCT has a bandwidth of 0.5 – 80 MHz (at -3 dB) with a transfer ratio of 1:10. The PD signals measured by HFCT were recorded using a digital storage oscilloscope at a sampling rate of 2.5 GS/s. The measurements were done in the form of single PD pulses of a suitable length (5 µs time window), capturing the pulse completely. The measured data was transferred to the personal computer to carry out the data processing as described in the next sections.

III. PD CLASSIFICATION METHODOLOGY

This section describes the methodology applied for PD signals classification. In order to determine the classifiers performance/classification results, the KPIs are also presented.

A. Features Extraction

Wavelet Transform is widely applied in the signal processing/ machine learning field to extract useful features for classification purposes. There are many types of the wavelet transform, such as continuous and discrete wavelet transform [5]. In this paper, DWT is chosen due to its ability of providing PD pulse information in time and frequency domains at specific frequency ranges. The DWT consists of high pass and low pass filters, which decompose the PD pulses into series of detailed and approximate coefficients. The decomposition process is an iterative technique in which the approximate component is further decomposed to extract the new approximate and detailed coefficients. The decomposition process is shown in Fig. 3, in which cA denotes approximate component and cD represents detailed component [8].

For the classification of PD sources (corona, internal and surface discharges), suitable features are extracted using DWT and statistical parameters.

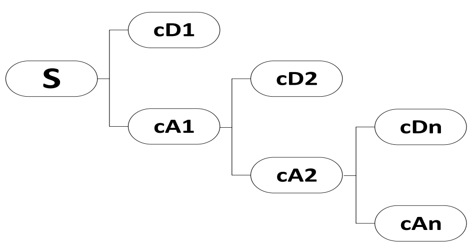


Fig. 3. DWT and its decomposition process [8]

At first, the DWT Sym type 7 technique is used on the recorded PD pulses in order to decompose the pulses until level 4 to extract the approximate (cA) and detailed (cD) coefficients. Furthermore, statistical parameters (Mean, Standard Deviation, Skewness and Kurtosis) are applied to each coefficient [9]. The statistical parameters (Skewness and Kurtosis) are defined as:

$$Sk = \frac{\sum_{i=1}^{N}(xi-\mu)^3 f(x_i)}{\sigma^3 \sum_{i=1}^{N} f(x_i)} \tag{1}$$

$$Ku = \frac{\sum_{i=1}^{N}(xi-\mu)^4 f(x_i)}{\sigma^4 \sum_{i=1}^{N} f(x_i)} - 3 \tag{2}$$

The above-defined statistical parameters (Skewness and Kurtosis) can be calculated with reference to normal distribution. The skewness shows the measure of the asymmetry of data with respect to the normal distribution, while Kurtosis indicates the sharpness of distribution [5][6].

The extracted features are shown in Table I, while the decomposition process of one corona signal (original signal, decomposed approximate and detailed coefficients until level 4) is shown in Fig. 4.

In Fig. 4, the cA denotes the approximate component while cD presents the detail component. The numbers of these components (cD1, cD2, cD3, cD4 and cA4) show the level of decomposition process. Here the approximate component is shown only at level 4 because the approximate component at previous levels (1,2 and 3) is further decomposed into approximate and detailed components.

After extracting the suitable features, the next step is classification. For classification, there are a number of supervised and unsupervised MLAs which are extensively used in the machine learning field for classification [5]. Unsupervised MLAs are used when the labels (source type) of data are unknown, while supervised algorithms are used when the labels are known. The choice of the algorithm depends upon the performance of an algorithm.

TABLE I. FEATURES EXTRACTED FOR TRAINING AND CLASSIFICATION

No.	Feature
1	Mean (cD1)
2	Standard Deviation (cD1)
3	Skewness (cD1)
4	Kurtosis (cD1)
5	Mean (cD2)
6	Standard Deviation (cD2)
7	Skewness (cD2)
8	Kurtosis (cD2)
9	Mean (cD3)
10	Standard Deviation (cD3)
11	Skewness (cD3)
12	Kurtosis (cD3)
13	Mean (cD4)
14	Standard Deviation (cD4)
15	Skewness (cD4)
16	Kurtosis (cD4)
17	Mean (cA4)
18	Standard Deviation (cA4)
19	Skewness (cA4)
20	Kurtosis (cA4)

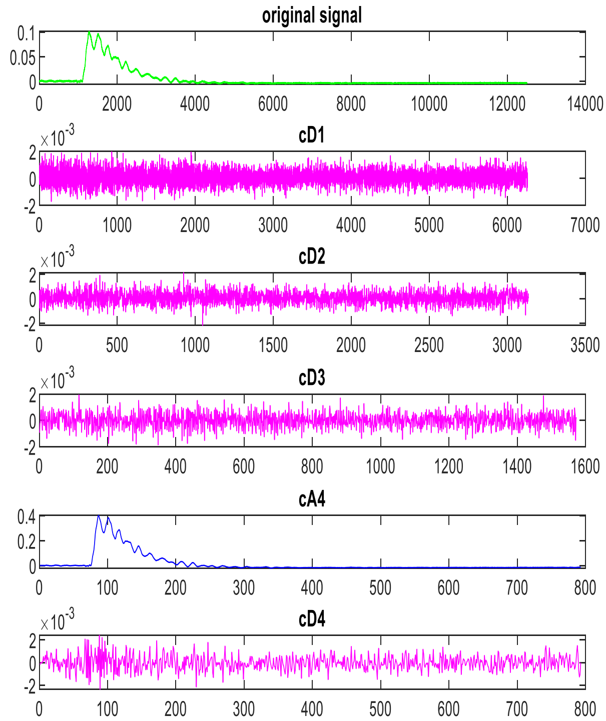


Fig. 4. Corona and its decomposition process

Some algorithms perform better on a large number of data sets, while other work efficiently on small data sets and the given input features. The most challenging task and time-consuming part of the machine learning field are to determine or identify the most suitable features which provide high classification accuracy and low processing time. For that, many researchers try different features and then choose the features which provide high classification performance [10][11]. This paper demonstrates that the extracted features provide satisfied classification results (accuracy) for the chosen algorithms.

B. *Training Data*

The selected database consists of 96 data sets to classify above mentioned three types of PD signals and to create the prediction model using MLAs. This prediction model could be used in the future as a reference model for classifying different types of PD signals. Hence, this model will be trained and tested with a greater number of data sets for determining its significance.

The used database contains three equal numbers of data sets (signals) for each type of PD source. There were a greater number of data sets for some PD sources, but since one of the PD sources had 32 data sets, we selected an equal number of data sets for classification, i.e., 32 for each type of PD source. One reason for choosing an equal number of data sets (recorded events) is that some MLAs perform better (gives high accuracy) on an equal number of signals. In future, we will collect a greater number of data sets of equivalent size to investigate the performance of the selected algorithms further.

For training the model, we have used 96 observations, size 21 kB, predictors 20, response class 3, cross fold validation (fold: 5fold), and the model is trained in MATLAB environment. The cross-validation is chosen to avoid the overfitting of data by dividing the data into folds, and then accuracy is determined for each fold. The system that is used for this purpose is AMD Ryzen 3 Pro 3300U/Radeon Vega Mobile Gfx 2.10 GHz, 16 GB RAM, 64-bit operating processor. In section I, a number of MLAs are highlighted that are used for different applications in [5]-[6]. In this paper, KNN and SVM algorithms have been compared. These algorithms are chosen based on their higher accuracy for the given set of features of the PD signals.

C. *Classification Algorithms*

SVM is widely used as a binary linear classifier in the machine learning field to classify the space into two classes by drawing a decision boundary line between data points using suitable support sectors. SVM can be used and modified for multiclass separation in many ways (One v/s One, One v/s All) [5].

The k-nearest neighbor algorithm is based on a similarity measure between data points. It calculates the Euclidean distance between input data points and picks the k closest points from the data set. After selecting the k closing points, it sets the predicting point for the new input data points. The challenging part of this MLA is to select the right number for k, which can result in lower accuracy and higher computation time [12].

D. *Key Performance Indicators (KPIs)*

KPIs are essential parameters to evaluate the performance of MLAs. This section describes the KPIs that are used in this paper for evaluation purposes.

a) Accuracy: It is one of the matrices in the data science field to evaluate the performance of classifier/MLA. This term is also known as overall accuracy and refers to the correct classification rate.

$$OA = \frac{TP + TN}{TP + FN + TN + FP} \times 100\,\% \tag{3}$$

The accuracy indicator is based on four terms; TP, TN, FP and FN. TP stands for True Positive, and this term is used for correctly classified or detected signals, while FP stands for False Positive and presents the incorrectly classified or detected signals. FN is the terminology of False Negative to exhibits incorrectly rejected signals, whereas TN is the abbreviation of True Negative that indicates correctly rejected signals. In addition to accuracy, these four terms (TP, TN, FN, FP) can be presented in different ways as performance indicators to declare the performance of the classifier. One example is the confusion matrix that is based on these four terms [13].

b) Prediction Speed: This KPI is used to calculate the computational cost of classifier /MLA. In simple words, it calculates the speed of the classifier for the prediction of the given task. The prediction speed is measured in observation/second (obs/sec).

c) Training Time: The training time can be defined as the time taken by the classifier to train the model/classifier. The training time varies from classifier to classifier.

IV. Results and Discussion

In this section, a thorough comparison between MLAs (SVM and KNN) of different types is carried out for understanding their performance in classifying different PD signals. To differentiate the models/types of MLAs (KNN and SVM) on basic level based on prediction speed, Table II is presented in this paper.

For obtaining the results of classification models, we have used a 5-fold cross-validation process to find the accuracy and other KPIs. The results of this comparison (using KPIs) for different MLAs are shown in Table III.

Based on the collected PD signals and extracted features, the MLAs were trained to classify PD signals of different sources (corona, internal and surface discharge). The input data set consists of a features vector (20 features) for each PD signal which is shown in Table I.

From Table III, it can be seen that the prediction speed of the SVM classifier (for all types) is less than that of KNN (for all types). The prediction speed of SVM is between 370 obs/sec to 940 obs/sec, while the prediction speed of KNN is between 920 obs/sec to 1900 obs/sec.

Regarding the training time of selected MLAs, there is no big difference between KNN and SVM classifiers. The training time for both algorithms (SVM and KNN) for all types is between 18 sec to 21 sec. Generally, training time is not an essential indicator compared to classification time for practical applications because training is performed offline and required only once.

The classification accuracy of SVM classifiers is 100%, except with SVM (Fine Gaussian) classifier. In contrast, the classification accuracy of KNN classifiers is between 80% and 90%, except with the KNN Coarse classifier, whose classification accuracy is 31.3%.

TABLE II. GENRERAL COMPARISON OF CLASSIFICATION MODELS BASED ON PREDICTION SPEED

Model Type	Prediction Speed
KNN (Fine KNN)	Medium
KNN (Medium KNN)	Medium
KNN (Coarse KNN)	Medium
KNN (Cosine KNN)	Medium
KNN (Cubic KNN)	Slow
KNN (Weighted KNN)	Medium
SVM (Linear)	Fast (Binary class) Medium (Multiclass)
SVM (Quadratic)	Fast (Binary class) Slow (Multiclass)
SVM (Cubic SVM)	Fast (Binary class) Slow (Multiclass)
SVM (Fine Gaussian)	Fast (Binary class) Slow (Multiclass)
SVM (Medium Gaussian)	Fast (Binary class) Slow (Multiclass)
SVM (Coarse Gaussian)	Fast (Binary class) Slow (Multiclass)

The best model for KNN MLA to classify PD signals is Fine KNN with an accuracy of 87.5%, while all models of SVM MLA provide 100% accuracy except with SVM (Fine Gaussian). Therefore, the selection for the best model of

SVM could be made based on higher prediction speed and lower training time. Based on the performance of the investigated classification models shown in Table III, the SVM (Medium Gaussian) model can be considered as the best model in our case with a prediction speed of ~ 940 obs/sec and training time of 19.293 sec.

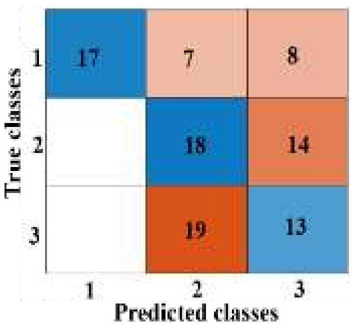
TABLE III. COMPARISON OF CLASSIFICATION MODELS

Model Type	Prediction Speed	Training Time	Accuracy
KNN (Fine KNN)	~ 1500 obs/sec	20.592 sec	87.5%
KNN (Medium KNN)	~ 1600 obs/sec	20.29 sec	83.3%
KNN (Coarse KNN)	~ 1500 obs/sec	19.845 sec	31.3%
KNN (Cosine KNN)	~ 920 obs/sec	20.692 sec	84.4%
KNN (Cubic KNN)	~ 1500 obs/sec	20.515 sec	80.2%
KNN (Weighted KNN)	~ 1900 obs/sec	20.298 sec	82.3%
SVM (Linear)	~ 630 obs/sec	18.36 sec	100%
SVM (Quadratic)	~ 400 obs/sec	19.356 sec	100%
SVM (Cubic SVM)	~ 370 obs/sec	19.082 sec	100%
SVM (Fine Gaussian)	~ 760 obs/sec	18.848 sec	50%
SVM (Medium Gaussian)	~ 940 obs/sec	19.293 sec	100%
SVM (Coarse Gaussian)	~ 820 obs/sec	18.929 sec	100%

Considering this paper, the following could be possible reasons/factors for affecting the classification accuracy of KNN and prediction speed of SVM:

- The demand for computational time of SVM is less than KNN due to its capability of handling larger dimensional data and classifying linear and non-linear signals in nature.
- KNN algorithm has the capability of performing well on a larger number of points (instances) and few dimensions.

TABLE IV. CONFUSION MATRIX FOR SVM (FINE GAUSSIAN)



Besides the accuracy, the confusion matrix is a crucial parameter to evaluate the performance of MLA. The confusion matrix for SVM (Fine Gaussian) is shown in Table IV.

In the confusion matrix, the true class shows the original labels of given PD signals of different sources (corona, internal and surface discharges), and the predicted class presents the labels obtained after applying SVM (Fine Gaussian) on given input features.

This confusion matrix is shown here to interpret the performance of the SVM-Fine Gaussian algorithm. In this confusion matrix, the correctly classified signals are depicted in major diagonal (blue boxes) and wrongly classified signals in minor diagonals. As it can be seen from the confusion matrix that the largest number of misclassified signals are shown for surface PDs with 19 signals, followed by corona PDs with 15 signals and then internal PDs with 14 signals. The internal and surface PD signals are misclassified with each other, while the signals of the corona PD source are misclassified with the signals of both (internal and surface) sources.

V. CONCLUSION

The identification of different types of PD faults is needed to carry out the maintenance strategy either to replace, repair or standby the components under observation. The development of automated solutions for PD identification provides improved solutions considering the speed and accuracy of the diagnostics. This paper shows the comparative analysis of different MLAs for classifying the signals of three different types of PD sources using suitable extracted features. The features were extracted using DWT and statistical parameters. Based on the selected features, different MLAs/prediction models were trained. In this paper, two MLAs (KNN and SVM) were trained, and their KPIs (accuracy, prediction speed and training time) were compared. From this comparison, it was found that SVM (with their different types) provided better results (in terms of training time and higher classification performance) than any type of KNN. The accuracy of all used classifiers of SVM is 100% except for SVM (Fine Gaussian) classifier, whose accuracy is 50%, and the confusion matrix shows the results (classified and misclassified signals) of this SVM (Fine Gaussian) classifier.

In future, a test environment will be created which will test all the features (one by one and later by increasing the number of features) for the selected machine learning algorithms. Besides testing features, different algorithms (in addition to these selected algorithms) will be tested on a constant feature environment. The test environment will be created for comparison purposes and for finding out the best methodology for our data.

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