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Methods for the classification and selection of extracted features of insulation defects from PD

***Abstract**. The aim of the paper is to investigate and compare the results of comparison of methods for classification and selection extracted features of insulation defects from partial discharges. For this purpose, the built-in functions MATLAB Classification Learner and Keras library were used. The results were compared using the machine learning algorithms SVM, KNN, CNN for four types of partial discharge defects.*

***Streszczenie.** W artykule przedstawiono wyniki badań oraz porównano rezultaty metod klasyfikacji i selekcji wyodrębnionych cech defektów izolacji pochodzących od wyładowań niezupełnych. W tym celu wykorzystano wbudowane funkcje MATLAB Classification Learner oraz bibliotekę Keras. Wyniki porównano przy użyciu maszynowych algorytmów uczenia SVM, KNN, CNN dla czterech rodzajów defektów izolacji. (**Metody klasyfikacji oraz selekcji wyodrębnionych cech defektów izolacji pochodzących od WNZ**).*

Keywords: CNN, PD, selection of features.
Słowa kluczowe: Konwulsyjne sieci neuronowe, WNZ, selekcja wyodrębnionych cech,

Introduction

One of the most important insulation tests is the partial discharge level test. [1]. Its gradual ageing and degradation process may lead to damage to power equipment or cable lines. The ageing process of the insu-ation may lead to damage to the transmission lines and, as a consequence, cause life threatening and large financial losses.

Any new engineering design solution must meet the strict criterion of the standard for acceptable levels of PD. For equipment such as cable accessories or medium voltage switchgear, during continuous operation, the correct classification of a given type of insulation defect (internal or surface discharge) is a big problem. Over the years, significant progress in the field of artificial intelligence and especially machine learning has significantly improved the diagnostic process.

Specialists in the field of high-voltage technology and artificial intelligence are constantly working to improve and accelerate the correct classification of types of partial discharges. The development of AI and ML has led to many successes in this area, as evidenced by the large number of publications. In the literature there are many methods of classification such as Support Vector Machine (SVM), k-nearest neighbours (KNN), decision tree (DT) [2,3] and CNN (Convolutional Neural Networks). The authors believe that another problem worthy of attention is the way in which the features are selected in case of a small amount of data. Continuous operation of electrical equipment together with many external signals can effectively interfere with the correct measurement of PD levels.

The main intention of the study was to investigate and find the best method of classification for the available measurement data, and then to identify as few features as possible for correct classification. The results of the research are to form the basis for further research into other research objects. This will allow to design software for a universal capacitive sensor collecting a certain amount of data. For this purpose, the best known classification methods in the literature were used.

The measurement data were used from previous research by the authors [7]. The features derived from voltage signals coming from PD simulated in HV switchgear in gas isolation were used. Measurements of location, dispersion and concentration have been extracted.

The article consists of the following parts: First of all, all features and types of insulation defects on which the process of learning algorithms was based were presented. The next stage describes the prepared test program and research process. Finally, the results of the learning process are presented together with conclusions and further guidelines for future research.

Measurement data

The analysed measurement data were obtained during measurements in the High Voltage Laboratory of the Warsaw University of Technology. Four different defects were simulated: high-potential needle, Degraded insulation system, low-potential needle and free-potential conductive material. Signals coming from the supply voltage and TEV sensor placed in a metal sheet, simulating a switchgear wall, were recorded. The measurement data was normalized and subjected to a digital filtering process. Then the signal was denoised by the wavelet transform (WT). 68 extracted features (16 types) describing voltage amplitude and phase for positive and negative signal polarization were extracted. The PRPDA method [6] listed in the Table 1 was used.

Table 1. Features of the partial discharge image used during research

Feature type	
Position	Quantile
	Median
	Tertiles
	Arithmetic average
	Mode
Distraction	Variance
	Standard deviation
	Average deviation
	Quarter deviation
	Classic coefficient of variation
	Skewness
	Pearson's first skewness coefficient
	Pearson's second skewness coefficient
	Skewness indicator
Concentration	Kurtosis
Other	Number of pulses

Prepared test program

The following options for the extracted features were used in the research:

Table 2. Applied number of extracted features during each research

No.	Number of features	Types	Polarization
1	10	A	p
2	10	A	n
3	10	P	p
4	20	A	p, n
5	68	A, P	p, n

where: a - amplitude values, b - phase values, p - positive polarity, n - negative polarity

The following Matlab Classifier Learning algorithms were used: Decision Tree, Bayes Classifier, Support Vector Machine and Nearest Neighbour Classifiers.

Before the classification, the cross-validation parameter k = 5 has been defined. Data was divided into test and train set. In the following, the types of individual classification algorithms were selected.

Table 3. Matlab classifiers used [4]

Algorithm type		Description
Support Vector Machine	Linear	Low model flexibility, a simple linear separation between classes
	Quadratic	2nd degree polynomial
	Cubic	3rd degree polynomial
	Fine Gaussian	High model flexibility — decreases with kernel scale setting. Finely detailed distinctions between classes, with kernel scale set to √P/4
	Medium Gaussian	Medium model flexibility, medium distinctions, with kernel scale set to √P
	Coarse Gaussian	Low model flexibility, coarse distinctions between classes, with kernel scale set to 4√P , where P is the number of predictors.
K-Neareast Neighbour	Fine	Finely detailed distinctions between classes. The number of neighbours is set to 1.
	Medium	Medium distinctions between classes. The number of neighbours is set to 10.
	Coarse	Coarse distinctions between classes.The number of neighbours is set to 100.
	Cosine	Medium distinctions between classes, using a Cosine distance metric. The number of neighbours is set to 10.
	Cubic	Medium distinctions between classes, using a cubic distance metric. The number of neighbours is set to 10.
	Weighted	Medium distinctions between classes, using a distance weight. The number of neighbours is set to 10.

The research results

The following diagrams show the effectiveness of each processes. The Classifier Learner application carries out the process of training and testing all types of algorithms in parallel.

A. SVM algorithm

For SVM algorithm the best result was obtained for the Quadratic type. The result of the Cubic and the Gaussian Medium were similar. For ten selected features the Cubic method result was the best, and for twenty and sixty-eight the Quadratic achieved algorithm. In the category of ten selected features, extracted features with positive polarization describing the position in relation to the supply voltage reached the highest efficiency of 85%.

B. KNN algorithm

For the k-nearest neighbour algorithm, Fine method achieved the best result. In this case, ten traits reached similar values, nearly 80% and twenty extracted features 85.5%.

The Classifier Learner application allowed to check the point distribution of all data. This allowed to find out where the classifier has assigned the data to the class correctly or incorrectly.

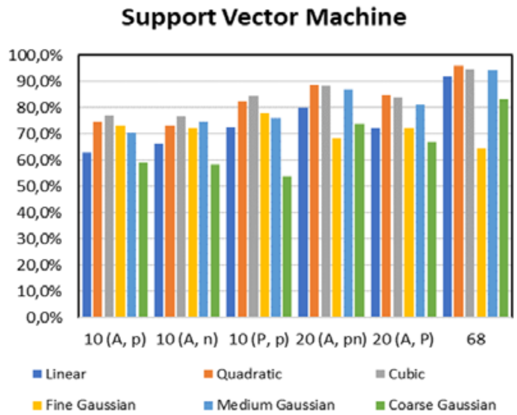

Fig. 1 Effectiveness of individual SVM classification algorithms depending on the number of extracted features

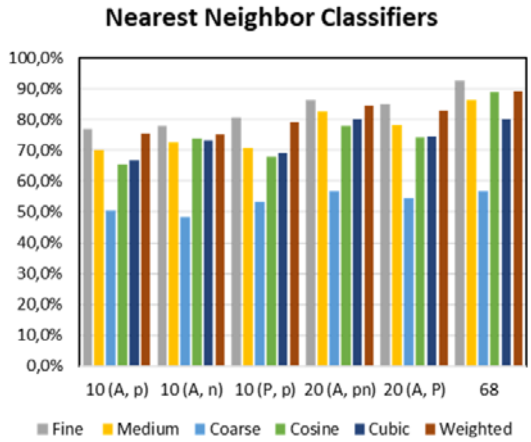

Fig. 2 Effectiveness of particular KNN classification algorithms depending on the number of extracted features

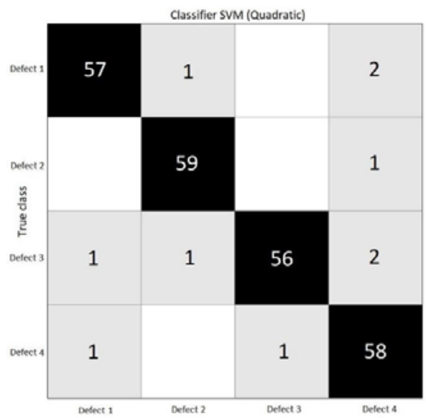

Fig. 3 Distribution matrix of classes in the process of recognition of partial discharge forms for 68 features classified by the SVM Quadratic algorithm

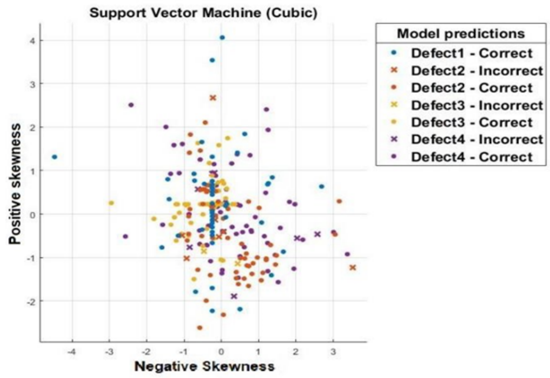

Fig. 4 Point distribution of the skewness

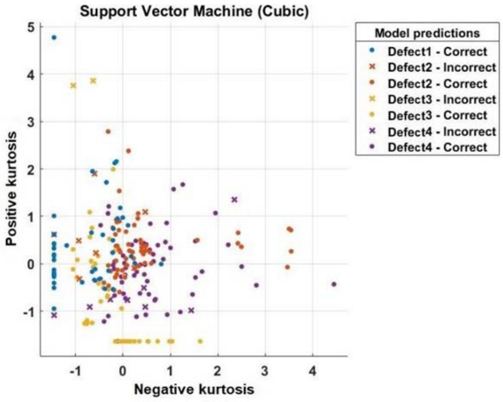

Fig. 5 Point distribution of the kurtosis

C. CNN algorithm

After first research, next one was carried out to check the effectiveness of convulsion neural network classification. The same measurement data was used, i.e. the previously extracted features in different configurations. The algorithm was developed by using the Keras library. The effectiveness of learning was checked depending on the number of features and activation functions. One hidden layer of 512 nodes was used.

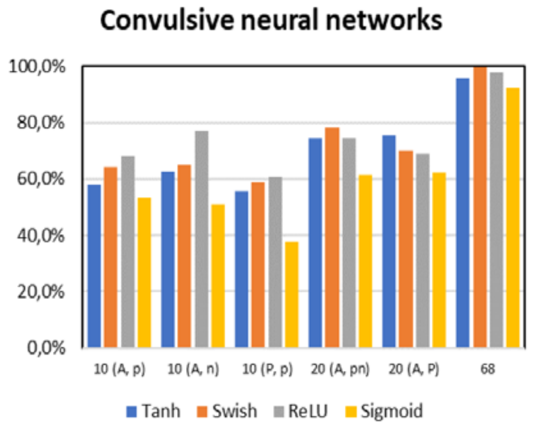

Fig. 6 Effectiveness of individual CNN classification algorithms depending on the number of extracted features

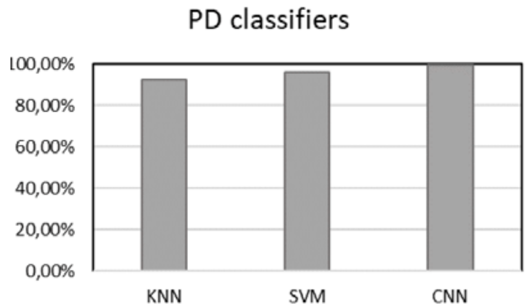

Fig. 7 The effectiveness of each tested method of classifying defects, due to partial discharges, for all features

D. Selection of the features

In the further step of the research, the algorithms that were able to select a minimum set of features while maintaining the highest classification efficiency were used. RefiefF, stepwise fit and fsrnca functions built-in MATLAB environment were chosen. First, stepwise fit and fsrnca algorithms were used to find the most significant features.

Table 4. Impact of a single extracted feature on the recognition of defects using the stepwise fit function

No of defects	0	1	2	3	4
Feature number	1, 3, 4, 5, 6, 8, 15, 16, 18, 20, 21, 23, 25, 27, 29, 32, 36, 38, 42, 55, 56, 61, 62, 63, 64, 67, 68	2, 9, 10, 13, 14, 17, 19, 22, 26, 28, 30, 31, 34, 35, 37, 39, 41, 44, 47, 48, 51, 52, 53, 58, 59, 65	7, 12, 24, 33, 40, 43, 45, 46, 50, 54, 66	11, 57	60

Table 5. Impact of a single extracted feature on the recognition of defects using the fsrnca function

No of defects	0	1	2	3	4
Feature number	2, 4, 5, 6, 10, 12, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 26, 27, 28, 36, 38, 40, 41, 42, 45, 50, 51, 54, 55, 56, 57, 59, 65, 66	1, 3, 25, 31, 43, 47, 48, 53, 58, 62	8, 9, 11, 13, 29, 30, 33, 35, 39, 46, 49, 52, 61, 63, 64, 67	7, 32, 34, 37 44, 60, 68	14

Both functions demonstrated that not all features are significant for the correct classification of insolation defects. Next, the reliefF function was used for all four defects to find the most relevant features in order of importance.

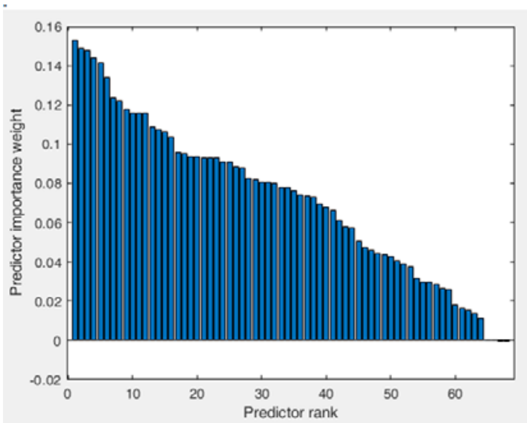

Fig. 8 Weight distribution of the individual feature of the data for the refiefF function

As can be seen in the above distribution, sixteen types of extracted features reached a weight higher than 0.1. These features were then moved to the convolutional neural network algorithm, which allowed to achieve a result of 95.7%, close to sixty-eight from previous research.

Conclusions

The presented article was intended for analysis of classification effectiveness, depending on the amount of data - extracted features of voltage signal from PD. In the research, built-in algorithms of the MATLAB Classifier Learner package and CNN algorithm of the Keras library were used. The MATLAB program allowed to carried out many parallel training and testing processes for different types of classifiers. The highest efficiency of the Support Vector Machine classification was achieved by the Quadratic method, and for k-nearest neighbors Fine - 92.5%. The highest efficiency of PD defect classification on the same measurement data was achieved by the Convolutional Neural Network algorithm, where the result was 100%.

Extracted features of the signal selected manually did not achieve satisfactory classification results. Better results were achieved using the built-in functions of MATLAB environment - fsrnca, stepwise fit and relief. Even sixteen of all sixty-eight features allowed to achieve high efficiency about 96% with convulsive neural networks algorithm.

In order to design a universal capacitive sensor, in the future, authors plan to conduct further research for other electrical objects and checking the effectiveness of the classification of partial discharge defects, depending on the amount of features.

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