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Research Paper

The Application of Selected Hierarchical Clustering Methods for Classification the Acoustic Emission Signals Generated by Partial Discharges

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The paper presents the results of the application of the hierarchical clustering methods for the classification of the acoustic emission (AE) signals generated by eight basic forms of partial discharges (PD), which can occur in paper-oil insulation of power transformers. Based on the registered AE signals from the particular PD forms, using a frequency descriptor in the form of the power spectral density (PSD) of the signal, their representation in the form of the set of points on plane XY was created. Next, these sets were subjected to analysis using research algorithms consisting of selected clustering methods. Based on the suggested numeric performance indicators, the analysis of the degree of reproduction of the actual distribution of points showing the particular time waveforms of the AE signals from eight adopted PD forms (PD classes) in the obtained clusters was carried out. As a result of the analyses carried out, the clustering algorithms of the highest effectiveness in the identification of all eight PD classes, classified simultaneously, where indicated. Within the research carried out, an attempt to draw general conclusions as to the selection of the most effective hierarchical clustering method studied and the similarity function to be used for classification of the selected basic PD forms.

Keywords: acoustic emission method; acoustic signals; partial discharges; power transformer; clustering method.

1. Introduction

Damages of high power transformers, the function of which is the transformation of electrical energy at various voltage levels, is, next to the dominant role of catastrophic atmospheric conditions, one of the essential causes of the power system failures. A significant part of the general number of power transformer failures, about 40%, is connected with various types of damages to the insulation system. These are typical internal damages caused by the occurrence of coil short-circuits due to, among others, local decrease of endurance of electrical insulation. This phenomenon is caused directly by the occurrence of partial discharges (PD) in these places, the causes of which may be as follows: damage of the cellulose insulation of the active part; the presence of dissolved gas inclusions in oil; also improper drying, degassing and impregnation of the insulating paper. Other causes of power transformer damages, which constitute about 18% of their general number, also include dampness of the electrical insulating oil leading to PD occurrence in gas bubbles at the voltage lower than the rated voltage, and also the occurrence of local electrical discharges in the areas of the irregular distribution of electric filed, connected with the application of dielectrics of various values of dielectric permittivity – development of surface partial discharges (SPD). Hence, the development of PD of various types can be the cause of over 50% of all power transformer failures, and detection and recognition of these phenomena play a key role in ensuring their continuous and failure-free operation (Cichoń, 2013; Kapinos *et al.*, 2014).

For the assessment of the technical condition of power transformers about PD detection in their insulation system, the engineering practice suggests using many diagnostic methods, including, among others, the electric method (measurement of the apparent charge) or the dissolved gas analysis (DGA) (Akbari et. al., 2010; Boczar et. al., 2014; Kazimierski, Olech, 2013). Also, the so-called supplementary methods, which include, among others, the acoustic emission (AE) method, have been used successfully for many years. The AE method is used mainly for detection, location, and intensity assessment of PD occurring in the insulation system of the transformers strategic for the system. Presently, the very method of the AE measurement taking is recognized to a significant degree, especially in the scope of inferences and the ways of their elimination (Olszewska, Witos, 2012; Rubio-Serrano et al., 2012; Soltani et al., 2012). Current works on the development of this method are directed towards the attempts to find effective mechanisms of the analysis of the measurement results obtained, in particular for effective identification of the particular PD forms and referring them to the assessment of the degradation degree of the transformer insulation system. So far, the attempts to identify basic PD forms have been carried out using for this purpose the results of frequency and time-frequency transformations of the AE signals measured, which were then analyzed using statistical and correlation methods, and also the elements of artificial intelligence (Boczar, 2001; Borucki et al., 2007; Fuhr, 2005; Lalitha, Satish, 2002).

The area of interest in the subject of clustering for the analysis of EA signals from PDs is, among others publication (Castro Heredia, Rodrigo Mor, 2019), in which the authors note that contemporary digital measurement systems of the electrical discharges allow you to isolate and create certain clusters and then link them to specific PDs sources. For this purpose, the authors of the publication propose the use of clustering methods based on spatial density, including DPC (*Density Peak Clustering*) and DBSCAN (*Density-based Spatial Clustering of Applications with Noise*). In the publication (Rodrigo Mor et al., 2017) it was proposed for example to use clustering methods to try to separate and distinguish between PD sources. The identification of defects in the insulation system of high voltage devices based on the clustering of acoustic signals from PD is also presented in the publication (Radionov et al., 2015). The authors of this publication state that by appropriate positioning of the periodic acoustic signal and based on the SCM (*Subtractive Clustering Method*) clustering technique, it is possible to identify selected main insulation defects of the transformer. The use of the SCM clustering method as a mechanism of the inference expert system was proposed by the authors of the publication (Mohan Rao et al., 2015). According to the authors of the publication, the expert system based on the SCM clustering method is characterized by high efficiency in identifying the modeled damage and good accuracy of decisions made. In the article (Chia-Hung et al., 2009) the authors presented the concept of using GCA (*Gray Clustering Analysis*) clustering methods to analyze the concentration of gases dissolved in the insulating oil of the transformer, which was determined by the DGA (*Dissolved Gas Analysis*) method. Based on the conducted research, it was found that the use of the GCA method in the DGA analysis is characterized by higher efficiency in identifying faults in the transformer insulation system, compared to solutions based on AI (*Artificial Intelligent*) techniques.

Probabilistic neural networks (PNN) and the method of clustering fuzzy C-means (FCM) for classification of PD in isolation of circuit breakers with SF_6 gas were proposed by the authors of the publication (Ming-Shou et al., 2014). During the conducted experiments on the identification of the modeled defects of the tested circuit breaker, the authors confirmed the high efficiency of classification of the measured PD using the proposed methods.

In the studies presented in this article, concerning the evaluation of the efficiency of classification of AE signals from eight PD forms using hierarchical clustering methods, the patterns of AE signals generated in laboratory conditions at the Laboratory of Diagnostics of Insulation Systems of the Opole University of Technology were used, using the prepared measuring system, shown in Fig. 1.

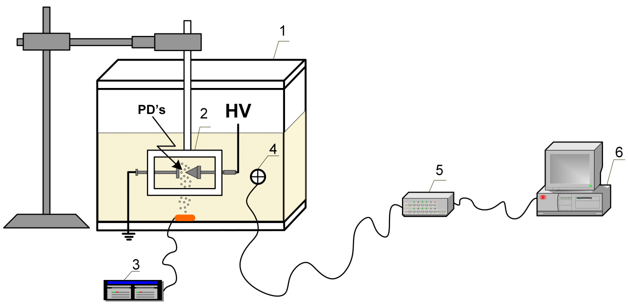

Fig. 1. Schematic diagram of the system used for the generation of PD and EA signals: 1 – transformer tank filled with electro–insulating oil, 2 – modeling spark gap, 3 – gas bubble generator (GP), 4 – measuring transducer, 5 – measuring amplifier and filter, 6 – a computer with measuring card.

For the generation of PD corresponding to various defects of paper-oil insulation of power transformers, a high-voltage test system was used, the main element of which was a single-phase TP60 type test transformer with a rated transmission ratio of 220/60.000 [V/V], using which appropriately selected modeling spark gaps was supplied. For the results of measurements and analysis of AE signals generated by the analyzed PD forms to be of general value and to allow for their comparison and reproduction, the value of the discharge generation voltage was 80% of the breakdown voltage (U_p) of each of the adopted modeling systems. During PD generation in the following systems: blade–blade and multi-blade–plate in gassed oil, an air bubble generator (GP) was used to generate gas bubbles. Its nozzle, which enabled the generation of bubbles reproducible in terms of shape and size, was placed under the above-mentioned. with spark gaps in such a way that the bubbles escaping on average every 0.1 s are located in the space between the electrodes of the spark gap. To record the EA signals generated by the PDA, a measuring circuit was used, consisting of broadband, differential, piezoelectric measuring transducer type WD AH17, by Physical Acoustics Corporation (PAC), a measuring amplifier AE Signal Conditioner with filtering systems, by EA System and a computer equipped with a measurement card type NI 5911 from National Instruments. Detailed information on the conditions of AE signals generated from the tested PD forms and the measuring equipment used are presented in the publications (Boczar *et. al.*, 2009; 2014; Borucki *et al.*, 2018; Kurtasz, 2011). To classify the recorded acoustic emission signals from the forms of partial discharges considered in the article, with the use of hierarchical clustering methods, the following designation of individual classes was adopted:

Class 1 – discharges in needle-to-needle setup in oil;
Class 2 – discharges in needle-to-needle setup in oil with gas bubbles;
Class 3 – needle-to-plane discharges in oil;
Class 4 – discharges in the surface setup of two flat electrodes with paper-oil insulation between them;
Class 5 – discharges in the surface set up with one flat electrode and the other multi-needle electrode with paper-oil insulation between them;
Class 6 – discharges in multi-needle-to-plane setup in oil;
Class 7 – discharges in multi-needle-to-plane setup in oil with gas bubbles;
Class 8 – discharges on particles with unspecified potential.

Figure 2 shows examples of time courses and averaged over one period of the supply voltage (T = 20 ms) spectral density of AE signals, which were recorded in laboratory conditions for each of the PD forms adopted by the authors.

2. Selection methodology of the AE signal parameter subjected to clustering

One of the statistical methods used for the classification and analysis of a big number of data is the so-called cluster analysis, i.e. clustering. This method is used mainly for the assessment and comparison of measurement results. Due to the lack of necessity to carry out the teaching process, it is also much faster than the methods based on artificial neural networks (ANN), neuro-fuzzy algorithms, and fuzzy logic. The use of clustering makes it also possible to classify a big number of measurement data simultaneously, in this case, PD classes, and to implement complex methods of the AE signal description in the calculation algorithms structure. From among five clustering methods described in the literature (Han *et al.*, 2012; Krzyśko *et al.*, 2008; Borucki *et al.*, 2018), the so-called hierarchical methods are mentioned most often, which, among others, include:

- single linkage method,
- complete linkage method,
- average linkage method,
- Ward's method.

The existence of separate areas, clusters possessing the property that any two objects belonging to the same cluster are similar to each other to a larger degree than two objects selected out of two different clusters indicates the existence of a structure in the dataset subjected to the process of clustering. Therefore, determining the similarity measure (function) between the objects remains a significant element of the clustering process, although in many situations it is more convenient to use the term of dissimilarity or nonprobability, e.g. distance. The most common measures of dissimilarity are as follows:

- the Euclidean Metric,
- the Standardized Euclid Metric,
- the Minkowski Metric,
- the City-Block Metric,
- the Mahalanobis Metric.

Selection of the set of features – representations of the objects under study is an important step in the clustering process of the AE signals from PD. In the case presented in this paper, the objects under study were AE signals from eight PD forms, out of which information in the form of a time waveform of the value of the discharge generation level of the length of 20 ms was separated. A characteristic of the power spectral density was determined for these waveforms, using the power spectral density (PSD) function normally available in the Matlab simulation and calculation environment, realized through $pwelch(D,\ f_p)$ instruction. On PSD images obtained, for each AE signal from a selected PD class, two weight values of spectral density for two frequency values were indicated, obtaining in this way a two-element vector, of which the first element was recognized as the so-called component X and the other as the so-called component Y – two coordinates in the Euclidean space. This process is shown in a diagram form in Fig. 3.

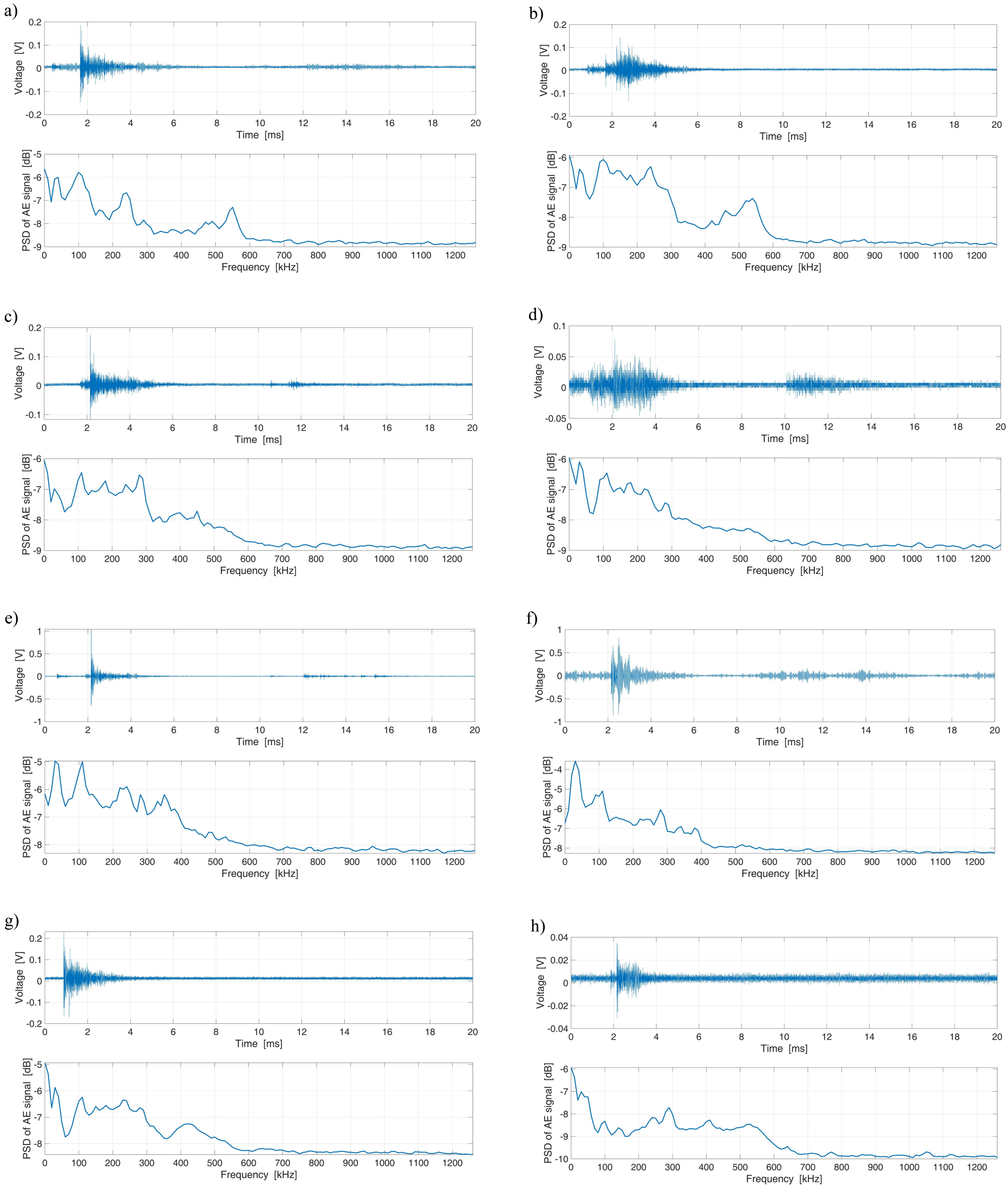

Fig. 2. Examples of time courses and averaged spectral power density of recorded AE signals from the analyzed forms of PD: a) Class 1, b) Class 2, c) Class 3, d) Class 4, e) Class 5, f) Class 6, g) Class 7, h) Class 8.

Coordinates of the points obtained in the way shown in Fig. 3 constituted a set of the following features – representation of the objects studied – AE signals from PD – and it was them that were subjected to further analysis using the above-mentioned clustering algorithms. The PSD frequency values for which the set of features was determined – the coordinates of the points imaging on the XY plane, the individual

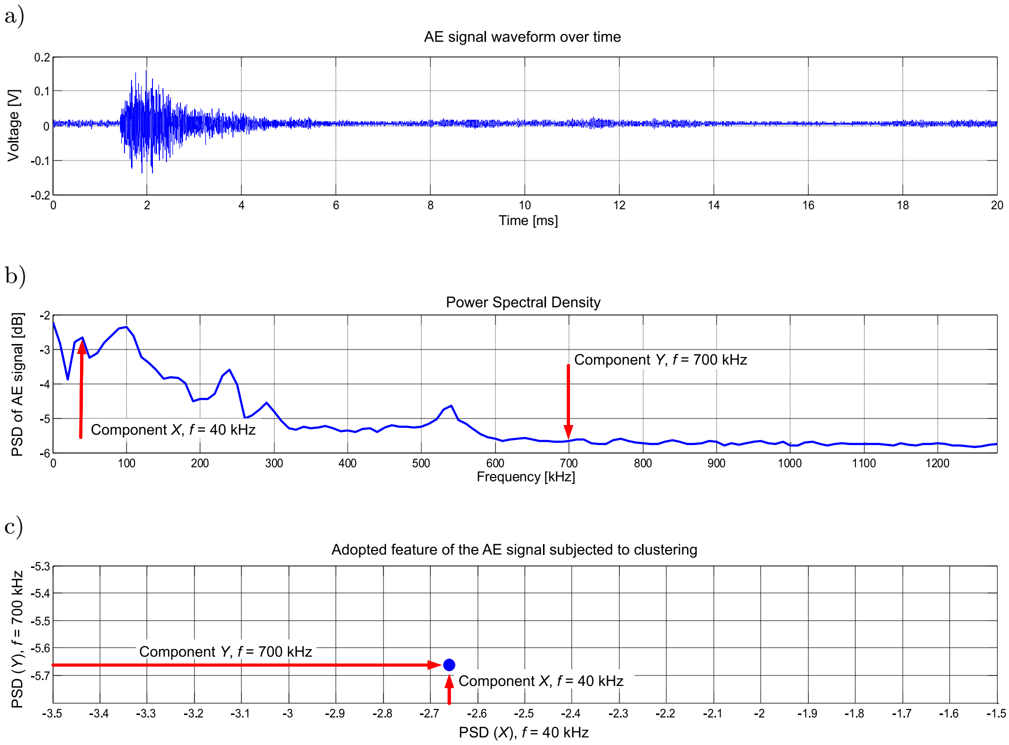

Fig. 3. Sample diagram of the procedure of determining the AE signal feature subjected to clustering: a) time waveform of the AE signal, b) PSD of the AE signal with two frequencies: X = 40 kHz, Y = 700 kHz, c) adopted feature of the AE signal subjected to clustering (coordinate XY).

time courses of the EA signals were experimentally selected from among 10,000 characteristics, which were determined for the PSD frequency pairs in the range 10–990 kHz, with a step of 10 kHz. The main indicator used to assess the quality of the selected PSD frequency pair was the distribution of points on the XY plane obtained as a result of its application, showing the individual studied AE waveforms in individual PD classes. Images with the highest possible degree of grouping were sought. The grouping result for the exemplary two pairs of PSD frequencies with values of 570 kHz for the X component and 670 kHz for the Y component and 40 kHz for the X component and 700 kHz for the Y component are shown in Fig. 4.

Under this article, 5 types of clustering were distinguished out of all images obtained. One PSD frequency pair was selected for each of them. The selected frequency pairs are listed in Table 1.

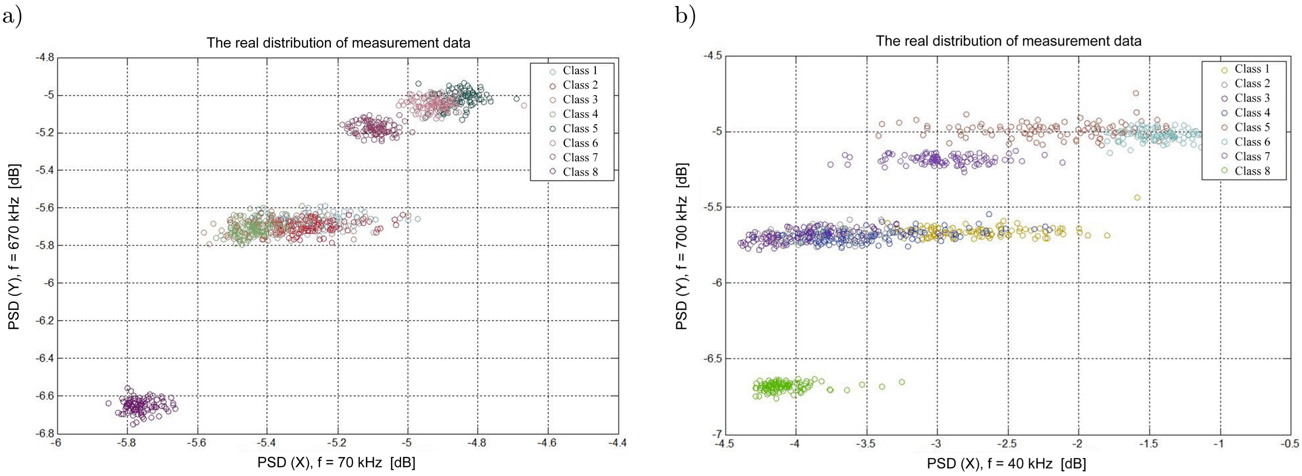

Fig. 4. Sets of points showing AE signals from PD for all tested PD classes and examples of PSD frequency pairs: a) with values of 570 kHz for the X component and 670 kHz for the Y component b) with values of 40 kHz for the X component and 700 kHz for the Y component.

Table 1. Listing of selected PSD frequency pairs.

Component X [kHz]	Component Y [kHz]
20	80
40	700
170	350
430	550
570	670

It should be stressed that a proper selection of the PSD frequency pairs had a key significance for the further research on the effectiveness of the research algorithms obtained because an unsatisfactory result of the clustering analysis could have been a consequence of an improper selection of the set of features describing an object, which turned out to have been non-representative (Morzy, 2013).

Within the research work carried out, the authors assessed the effectiveness of classification of the AE signals from eight PD classes for all the above-mentioned clustering methods and measures of dissimilarity. Nevertheless, due to a considerable number of the results obtained, only the most favorable results have been presented in the following chapters.

3. Adopted criteria of assessment of the effectiveness of the AE signals classification using the clustering methods studied and the results obtained

Combining the selected clustering methods, similarity functions, and also PSD frequency pairs of components XY, 140 clusterings (research) parameters were obtained. Their effectiveness was verified by analyzing a degree of reproduction of a real distribution of the points illustrating the particular time waveforms of the AE signals in the obtained clusters for 8 PD classes. Therefore, numeric parameters were determined – the so-called performance indicators, which included:

- modulus of the average difference $|\Delta\overline{x}|$, given as (for $n = 20$):

$$|\Delta\overline{x}| = \left|\overline{x}_{(\text{cluster})} - \overline{x}_{(\text{class})}\right| = \left|\frac{1}{n}\sum_{i=1}^{n} x_{n(\text{cluster})} - \frac{1}{n}\sum_{i=1}^{n} x_{n(\text{class})}\right|, \tag{1}$$

where $|\Delta\overline{x}|$ is modulus of the average difference, $\overline{x}_{(\text{cluster})}$ is arithmetic average of the weight values of spectral density for the cluster studied, $\overline{x}_{(\text{class})}$ is arithmetic average of the weight values of spectral density for the PD class studied, $x_{n(\text{cluster})}$ is n-weight value of spectral density in the cluster studied, $x_{n(\text{class})}$ is n-weight value of spectral density in the PD class studied;

- and modulus of standard deviations difference $|\Delta\sigma|$, given as (for $n = 20$):

$$|\Delta\sigma| = \left|\sigma_{(\text{cluster})} - \sigma_{(\text{class})}\right| = \left|\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(x_{n(\text{cluster})} - \overline{x}_{(\text{cluster})}\right)^2} - \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(x_{n(\text{class})} - \overline{x}_{(\text{class})}\right)^2}\right|, \tag{2}$$

where $|\Delta\sigma|$ is modulus of standard deviations difference, $\sigma_{(\text{cluster})}$ is standard deviation of weight values of spectral density for the cluster studied, $\sigma_{(\text{class})}$ is standard deviation of weight values of spectral density for the PD class studied WNZ, $x_{n(\text{cluster})}$ is n-weight value of spectral density in the cluster studied, $\overline{x}_{(\text{cluster})}$ is arithmetic average of the weight values of spectral density for the cluster studied, $x_{n(\text{class})}$ is n-weight value of spectral density in the PD class studied, $\overline{x}_{(\text{class})}$ arithmetic average of the weight values of spectral density for the PD class studied.

The modulus of the averages difference $|\Delta\overline{x}|$ and the modulus of the standard deviations difference $|\Delta\sigma|$ were calculated for the weight values of spectral density, determined for the real distribution of the PD classes studied and the distribution of clusters obtained as a result of clustering carried out, separately for component X and component Y. 20 weight values of spectral density were adopted for calculations, which were obtained from the analysis of contingency table of both distributions, using function *hist.* normally available in Matlab environment. The difference values obtained for component X and component Y were averaged using the mathematical average.

Taking into account the similarity of the indicators presented above, given with formulae (1) and (2), it was decided to combine them in the next step into the common indicator of quality assessment, which is an arithmetic average value, given as the following dependence:

$$\overline{\Delta} = \frac{\Delta x_{av} + \Delta\sigma_{av}}{2}, \tag{3}$$

where $\overline{\Delta}$ is averaged value of modules of averages difference and modules of standard deviations difference, Δx_{av} is averaged value of modules of averages difference for components X and Y, $\Delta\sigma_{av}$ is averaged value of modules of standard deviations difference for components X and Y.

Indicator $\overline{\Delta}$ obtained reflects the effectiveness of class reproduction in a cluster, at the same time ensuring taking into account both complementary effectiveness indicators – arithmetic average and standard deviation. The selection of the most effective representation of the adopted PD classes in the particular

Table 2. Listing of the results of PD class representation in the created clusters for a sample research algorithm Ward-Seuclidean-50/700 and selected three PD classes (classes 1, 3, 5).

Class	Cluster	Component	Indicator values in a class		Indicator values in a cluster		$\|\Delta\overline{x}\|$	$\|\Delta\sigma\|$	Δx_{av}	$\Delta\sigma_{av}$	$\overline{\Delta}$
			$\overline{x}$	σ	$\overline{x}$	σ					
1	**1**	***X***	**–3.15**	**0.5910**	**–2.79**	**0.3810**	**0.3550**	**0.2100**	**0.1794**	**0.1061**	**0.1428**
1	**1**	***Y***	**–5.58**	**0.0817**	**–5.57**	**0.0795**	**0.0038**	**0.0022**			
1	2	X	–3.15	0.5910	–3.90	0.2860	0.7540	0.3050	0.4325	0.1656	0.2991
1	2	Y	–5.58	0.0817	–5.69	0.0557	0.1110	0.0261			
1	3	X	–3.15	0.5910	–2.94	0.5470	0.2030	0.0442	0.4295	0.0323	0.2309
1	3	Y	–5.58	0.0817	–4.92	0.1020	0.6560	0.0204			
3	1	X	–4.05	0.1970	–2.79	0.3810	1.2600	0.1850	0.6875	0.1044	0.3960
3	1	Y	–5.69	0.0557	–5.57	0.0795	0.1150	0.0238			
3	**2**	***X***	**–4.05**	**0.1970**	**–3.90**	**0.2860**	**0.1510**	**0.0891**	**0.0755**	**0.0446**	**0.0601**
3	**2**	***Y***	**–5.69**	**0.0557**	**–5.69**	**0.0557**	**0.0000**	**0.0000**			
3	3	X	–4.05	0.1970	–2.94	0.5470	1.1100	0.3500	0.9390	0.1982	0.5686
3	3	Y	–5.69	0.0557	–4.92	0.1020	0.7680	0.0464			
5	1	X	–2.94	0.5470	–2.79	0.3810	0.1510	0.1660	0.4020	0.0943	0.2482
5	1	Y	–4.92	0.1020	–5.57	0.0795	0.6530	0.0226			
5	2	X	–2.94	0.5470	–3.90	0.2860	0.9570	0.2610	0.8625	0.1537	0.5081
5	2	Y	–4.92	0.1020	–5.69	0.0557	0.7680	0.0464			
5	**3**	***X***	**–2.94**	**0.5470**	**–2.94**	**0.5470**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**
5	**3**	***Y***	**–4.92**	**0.1020**	**–4.92**	**0.1020**	**0.0000**	**0.0000**			

clusters was made by indicating the smallest value of the indicator $\overline{\Delta}$ (Borucki, Łuczak, 2017; Borucki *et al.*, 2018).

Table 2 shows sample results of the experiment carried out, which were obtained for one of the analyzed clustering algorithms (*Ward-Seuclidean-50/700*) – Ward's clustering method, distance measures Standardized Euclid Metric and PSD components: X = 50 kHz, Y = 700 kHz – and three PD classes classified simultaneously (classes 1, 3, 5). The results characteristic of the highest representation indicator of the particular PD classes in the clusters obtained is marked in bold.

To carry out a conclusive assessment of the effectiveness of the research algorithms analyzed, an additional percentage was suggested – the so-called research algorithm efficiency, which bases on the comparison of the number of multiple indications of the most effective representation of the particular PD classes in a single cluster, and the repetition was counted from the consecutive indication and the number of PD classes analyzed. This indicator was given by the following dependence:

$$S = 100 - \frac{N_R}{N_C} \times 100 \ [\%], \tag{4}$$

where S – research algorithm efficiency, N_R – number of repetitions, N_C –number of PD classes analyzed.

The results of the research experiment carried out included the analysis of 140 clustering algorithms and eight PD classes occurring simultaneously. Based on the results obtained, it was found that maximum effectiveness for all algorithms assessed, determined in compliance with the percentage of the research algorithm

Table 3. Listing of the averaged value of the indicator $\overline{\Delta}$ for research algorithms of 87.5% efficiency in an increasing order.

No.	Research algorithm	The averaged value of the indicator $\overline{\Delta}$
1	Ward-Cityblock-570/670	0.0399
2	Complete-Cityblock-570/670	0.0403
3	Ward-Mahalanobis-40/700	0.0978
4	Ward-Euclidean-40/700	0.0998
5	Ward-Seuclidean-40/700	0.0998
6	Ward-Minkowski 0.3-40/700	0.1021
7	Ward-Minkowski 0.5-40/700	0.1030
8	Ward-Cityblock-40/700	0.1037
9	Complete-Seuclidean-40/700	0.1052
10	Complete-Minkowski 0.8-40/700	0.1096
11	Complete-Minkowski 0.5-40/700	0.1170
12	Ward-Mahalanobis-170/350	0.1865

efficiency (4) was 87.5%, which means that 7 original indications and 1 repetition. To indicate unambiguously a clustering algorithm showing the highest classification effectiveness of the PD forms analyzed, an averaged value of an indicator $\overline{\Delta}$ (3) was used additionally. The value of this parameter was determined for all algorithms studied, for which the percentage of the research algorithm efficiency was 87.5%. The results of the calculations carried out are shown in Table 3. The clustering algorithm of the highest classification effectiveness of the AE signals from PDs is the algorithm for which the averaged value $\overline{\Delta}$ is of the lowest number (Item no. 1, Table 3).

4. Conclusion

Based on the research carried out it was found that there exists the possibility of effective use of the hierarchical clustering methods for classifying the AE signals from PD. The analysis of the averaged value of the indicator $\overline{\Delta}$ for the particular research algorithms proved that the Ward-Cityblock-570/670 algorithm is characteristic of the highest effectiveness, which realizes Ward's clustering method, with the similarity function in the form of the City-Block Metric for the PSD frequency pair of 570 kHz for component X and 670 kHz for component Y ($\overline{\Delta}$ = 0.0399). A slightly higher value of the averaged indicator $\overline{\Delta}$ = 0.0403, thus slightly lower effectiveness, was obtained for the Complete-Cityblock-570/670 research algorithm realizing the clustering method of complete linkage with the similarity function in the form of the City-Block Metric for the same PSD frequency pair. Therefore, the two most effective research algorithms were based on the same similarity function – the City-Block Metric and the same PSD frequency pair of the values of 570 kHz and 670 kHz.

The analysis results of the averaged value of the indicator $\overline{\Delta}$ also showed that nine consecutive out of the remaining algorithms studied, beginning with the third most effective algorithm, were based on the same PSD frequency pair of the values of 40 kHz for component X and 700 kHz for component Y. This analysis result shows that the application of the PSD frequency pair of a big difference of the values between component X and component Y has a positive influence on the effectiveness of the clustering algorithm, which results in a more accurate representation of PD classes in the clusters created.

It should be also observed that all algorithms, for which the highest percentage of the research algorithm efficiency (4) – 87.5% was obtained in the experiment carried out, were based on two clustering methods: Ward's method – 8 research algorithms and the complete linkage method – 4 research algorithms. Hence, it can be concluded that these methods, in particular Ward's method, are the most suitable for carrying out the analyses aimed at the classification of basic PD forms in the datasets created for the selected PSD frequency pairs.

All similarity functions (the Euclidean Metric, Standardized Euclidean Metric, Minkowski Metric, City-Block Metric, and Mahalanobis Metric) selected for the research experiment, found their application in the research algorithms listed in Table 3, which indicates a smaller significance of the selection of similarity function in the algorithms tested compared with the clustering and the PSD frequency pair methods applied.

The research results presented in this article are based entirely on the analysis of standard AE signals, which were generated in the Laboratory of Diagnostics of Insulation Systems of the Opole University of Technology. The satisfactory results of classification of AE signals from PD forms modeled in laboratory conditions with the use of hierarchical clustering methods obtained in this article constitute the first stage of research in this direction. The next stage of scientific and research works will be the use of the proposed by the authors clustering methods for the analysis of EA signals recorded on real energy facilities, in particular power transformers.

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