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Using Clustering Methods for the Identification of Acoustic Emission Signals Generated by the Selected Form of Partial Discharge in Oil-Paper Insulation

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The article presents the results concerning the use of clustering methods to identify signals of acoustic emission (AE) generated by partial discharge (PD) in oil-paper insulation. The conducted testing featured qualitative analysis of the following clustering methods: single linkage, complete linkage, average linkage, centroid linkage and Ward linkage. The purpose of the analysis was to search the tested series of AE signal measurements, deriving from three various PD forms, for elements of grouping (clusters), which are most similar to one another and maximally different than in other groups in terms of a specific feature or adopted criteria. Then, the conducted clustering was used as a basis for attempting to assess the effectiveness of identification of particular PD forms that modelled exemplary defects of the power transformer's oil-paper insulation system. The relevant analyses and simulations were conducted using the Matlab estimation environment and the clustering procedures available in it. The conducted tests featured analyses of the results of the series of measurements of acoustic emissions generated by the basic PD forms, which were obtained in laboratory conditions using spark gap systems that modelled the defects of the power transformer's oil-paper insulation.

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

1. Introduction

The notion of maintaining fault-free operation of power transformers, which constitutes one of the crucial elements of a power system, remains one of the substantial problems in the contemporary power industry (Singh *et al.*, 2008; Boczar *et al.*, 2014). From an economic and technical point of view (Yadav *et al.*, 2008; Majchrzak, 2017; Borucki, 2009) it is justified, and even necessary, to search for and develop modern diagnostic methods, the primary purpose of which is early detection, localisation and assessment of the hazard of irreversible damage in the transformer's insulation system due to a defect developing inside its tank. Currently, classic diagnostic methods, amongst others, are being applied in this case: the so-called basic electrical methods (insulation resistance, capacity, dielectric loss measurements), gas chromatography (DGA) or the analysis of the transformer oil's physical and chemical properties (Akbari *et al.*, 2010; Basak, 1999; Borucki *et al.*, 2010; 2012; Kaźmierski *et al.*, 2013). The above methods are also becoming supplemented with the acoustic emission method (AE), which is being more commonly applied for crucial transformers operating in a power system, and which allows detecting, locating and assessing the intensity of partial discharges (PD) generated in their oil-paper insulation system. At the current stage of using the AE method for assessing PD's in the conditions of normal transformer operation, the problem is not the measurement execution itself (selection of measuring instruments and their metrological parameters, elimination of interference, etc.), but the correct analysis and interpretation of the recorded acoustic signals (Rubio-Serrano *et al.*, 2012; Soltani *et al.*, 2012; Rodrigo *et al.*, 2011; Olszewska *et al.*, 2012). The direction for future work on the development of the AE method, which is used in the diagnostics of transformer units, is the attempt to search for effective methods of analysing the obtained measurement results, among others, in order to effectively identify the so-called basic PD forms, which can be used to assess the degree of degradation of the insulation system. Until now, such attempts were executed based on the results of the frequency, time and frequency, statistical or correlation analyses. Artificial intelligence elements were also used to identify the basic PD forms (Boczar, 2001; Borucki *et al.*, 2007; Fuhr, 2005; Lalitha *et al.*, 2002). Due to the complexity of the diagnostic process, the use of the aforementioned methods required a relatively long time to process and analyse the obtained measurement results and often resulted in obtaining ambiguous results in terms of identifying the measured AE signals.

The article presents the results of an attempt to use the clustering methods to identify AE signals generated by laboratory-modelled PD's in oil-paper insulation. The conducted testing featured qualitative analysis of the following methods of clustering the recorded AE signals: single linkage, complete linkage, average linkage, centroid linkage and Ward linkage (Zalewski *et al.*, 1997). The purpose of the conducted analysis was to search the tested series of AE signal measurements, deriving from three various PD forms, for cluster elements, which are most similar to one another and maximally different than in other groups in terms of a specific feature or adopted criteria. The conducted clustering was used as basis for attempting to assess the effectiveness of identification of particular PD forms that modelled exemplary defects of the power transformer's oil-paper insulation system.

2. Considered forms of partial discharges and the measurement station

In order to obtain the models of AE signals generated by the basic PD forms, which occur in actual transformer insulation systems, the Insulation System Diagnostics Laboratory of the Opole University of Technology has prepared suitable modelling spark gaps. The spark gaps were immersed in insulation oil that filled the transformer tank and then were supplied with high voltage from the test transformer. As part of the conducted research, it was proposed to generate PD's and record the AE signals for three modelling spark gap systems:

- discharges in the blade-blade spark gap system immersed in oil, which may correspond to PD's that occur due to damage to the insulation of two adjacent transformer winding coils (highlighted as Class 1),
- discharges in the blade-plate spark gap system immersed in oil, which may correspond to PD's that occur between the damaged part of insulation of the transformer winding and the grounded flat parts, such as elements of the core, yoke, tank, magnetic screens (highlighted as Class 2),
- discharged in the surface spark gap system with one flat electrode, one multi-blade electrode, with oil-paper insulation between them, which may correspond to PD's that occur at the contact of copper wires and the oil-paper insulation system, which features irregularities in the winding surfaces (highlighted as Class 3).

The insulation systems described above allowed generating PD's with the apparent charge Q_p in the scope of a dozen or so pC to approx. 2 nC (values confirmed using the electrical method). In order to maintain the overall quality of the obtained measurement results of AE signals from the measured PD's and for the analyses to enable comparing and reproducing, the value of the discharge generation voltage was adopted at 80% of the breakdown voltage (U_p) of each of the used modelling spark gaps. Figure 1 presents the diagram of the blade-plate spark gap system used for generating PD's and AE signal recording (Class 2).

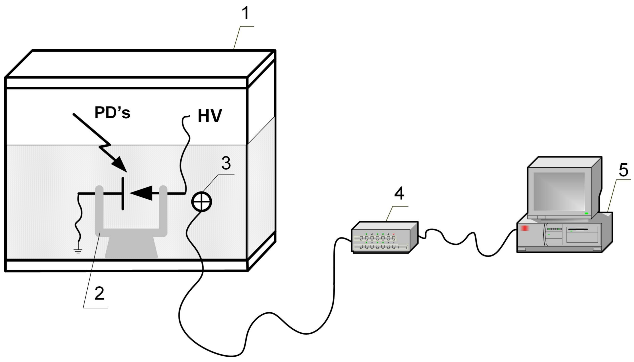

Fig. 1. Measurement system diagram: 1 – tank with insulation oil, 2 – modelling spark gap, 3 – measurement transducer, 4 – measurement filter and amplifier, 5 – computer and measurement card.

The AE signals generated by the PD's were measured using the WD AH17 type piezoelectric transducer from Physical Acoustics Corporation, mounted to the tank. The used transducer has a sensitivity of 55 ± 1.5 dB (in relation to V/ms^{-1}) and a transmission band of 100 kHz to 1 MHz in the range of $\pm$ 10 dB. In order to amplify the measurement signal, the transducer outputs were connected to the differential inputs of the AE Signal Conditioner amplifier from EA System. The amplifier featured a 40 dB amplification and a transmission band of 1 kHz $\div$ 2.0 MHz. The measurement system was additionally equipped with a band-pass filter with cut-off frequencies of 20 kHz and 1.0 MHz. The use of the aforementioned filtering band was necessary due to the necessity of eliminating interference signals present in the bottom and top frequency band, and to eliminate the aliasing phenomenon. The observance and recording of the measured AE signals was executed using a computer equipped with the NI 5911 measurement card from National Instrument. The measurements were conducted at the sampling frequency of 2.56 MHz and resolution of 14 bits.

3. Specification of the tested clustering methods

Data clustering, also known as grouping or cluster analysis, belongs to the methods of data exploration and machine learning related to document clustering. It is one of the methods of the so-called unsupervised learning, based on grouping of elements into relatively homogenous classes, the basis of which is the similarity between the elements, defined by the similarity function, known as metrics. The purpose of conducting the cluster analysis is the organisation of the observed data into coherent structures or groups by way of analysing the similarities in elements undergoing testing according to the adopted criteria. Particular elements included in the group should be as similar as possible and maximally different from the elements in other groups. In general, the clustering methods can be divided into hierarchical and k-means methods. The clustering methods used as part of the execution of this research include the following: single linkage, complete linkage, average linkage, centroid linkage, Ward linkage (Cichosz, 2000; Krzyśko *et al.*, 2008).

In the single linkage method, the distance between a newly created cluster and an external unit is defined as the smallest distance from the distances between the units in this cluster and the external unit. If we assume that in an n-dimensional space we have a set $X = \{x_i\}$, where x_i are the set elements and a point P, which does not belong to set X, then the distance of point P from set X is defined with the following formula:

$$d(P, X) = \min_i d(P, x_i). \tag{1}$$

In this method, the distance between two clusters is established as the smallest distance of the distances between the units from the first and second cluster.

In the complete linkage method, the distance between a newly created cluster and an external unit is defined as the biggest distance from the distances between units in this cluster and the external unit. For point P, which does not belong to set X, the distance of point P from set X is defined with the following formula:

$$d(P, X) = \max_i d(P, x_i), \tag{2}$$

where x_i are elements of set X in a n-dimensional space.

In the average linkage method, the distance between a newly created cluster and an external unit is defined as the arithmetic mean of the distances between the units in this cluster and the external unit. For point P, which does not belong to set X, the distance of point P from set X is defined with the following formula:

$$d(P, X) = \frac{1}{k} \sum_{i=1}^{k} d(P, x_i), \tag{3}$$

where k is the number of elements in set X.

In the centroid linkage method, the centroid is estimated for each of the groups – as the mean value of all objects (vectors) belonging to the given group. The distance between the clusters is defined as the distance between the cluster's centroids. The main concept of this algorithm is the specification of the k centroids – for each of the groups, and then assignment of all the objects to the nearest centroid – creation of k – clusters. In the next algorithm cycle, each of the initially obtained clusters will feature the estimation of new centroids and the objects are distributed anew. The operation is repeated until no object changes the assigned cluster.

In the Ward linkage method, two groups of objects are merged into a single group to minimise the sum of squared deviations of all objects in the two groups from the centre of gravity of the new group created as result of their merging. At each stage of merging, from all the applicable groups, merging is executed within groups that, as result, creates a group of objects with the smaller variation in terms of their characteristic variables.

An important element of the clustering process is the selection of the method of determining the similarity between the elements of the analysed sets, i.e. specification of the similarity function referred to as the metric. The following metrics are applied (Krzyśko *et al.*, 2008):

- Euclidean metric, defined with the following formula:

$$d(X, Y) = \left(\sum_{i=1}^{n} (x_i - y_i)^2 \right)^{1/2}, \tag{4}$$

  where X, Y are set points in an n-dimensional space, and x_i and y_i are the coordinates of those points,
- standardised Euclidean metric, defined with the following formula:

$$d(X, Y) = \left(\sum_{i=1}^{n} \frac{1}{\widehat{s}_i^2} (x_i - y_i)^2 \right)^{1/2}, \tag{5}$$

  where $\widehat{s}_i^2$ is a variation of the i point coordinate,
- Cityblock metric or Manhattan distance, defined with the following formula:

$$d(X, Y) = \sum_{i=1}^{n} |x_i - y_i|, \tag{6}$$

- Mahalanobis distance, also referred to as the weighted Euclidean distance, defined with the following formula:

$$d(X, Y) = \left((X - Y) \cdot C^{-1} \cdot (X - Y)^T \right)^{1/2}, \tag{7}$$

  where C is the covariance matrix:

$$C = \operatorname{cov}(X, Y), \tag{8}$$

- Minkowski metric, defined with the following formula:

$$d(X,Y) = \left(\sum_{i=1}^{n} |x_i - y_i|^p\right)^{1/p}, \tag{9}$$

where p is parameter which decides about importance of difference between objects on each clusters.

4. Analysis of obtained results

In order to attempt identifying the AE signals generated by three basic PD forms modelled in laboratory conditions using clustering tools, suitable numerical procedures were developed and implemented in the Matlab environment. The conducted testing featured a comparative analysis of all clustering methods specified in Sec. 3 and the relevant metrics (distance measures). As the parameter of the measured AE signal used in the clustering process, the authors have proposed the power spectrum density (PSD), which was determined for experimentally selected two limit frequencies, 90 kHz and 990 kHz, respectively. The following figures present the exemplary characteristics and histograms constituting the result of clustering of three basic PD forms, whereby Class 1 describes discharged in the blade-blade spark gap system immersed in oil, Class 2 – discharges in the blade-plate spark gap system immersed in oil, and Class 3 – discharges in a surface spark gas system. Figure 2a illustrates the original distribution of measurement data of AE signals from three PD forms under analysis, whereas Fig. 2b presents the distribution of the same measurement data, but as result of clustering conducted using the Ward and standardised Euclidean metric methods.

The analysis of the above figures demonstrated an accurate reconstruction, by way of clustering, of the analysed Class 3 data and high accuracy in the reconstruction of the Class 1 and 2 data layout. These conclusions are also confirmed by the analysis conducted by way of comparing the quantity of particular class elements for the original distribution of measurement data and the distribution obtained by way of clustering (Figs. 3–5).

The following figures present the histograms of the distribution of original measurement data, data subjected to clustering and the comparison of the quantity of particular elements for particular PSD values. Component X concerns the assessment of the variation of the AE signal defined for the streak of the power spectrum density with the frequency of 90 kHz, whereas component Y – for the PSD streak with the frequency of $f = 990$ kHz. Figure 3 illustrates the comparison of the quantity of Class 1 elements for the original data distribution and the distribution obtained by way of clustering; Fig. 4 – respectively for Class 2, whereas Fig. 5 – for Class 3. The histograms also present the PSD's mean value and standard deviation for particular data sets (original data and data subjected to clustering), as well as their dispersion measure – absolute difference of the Mean value Δ and standard deviation Δ (STD). The minimisation of the two above parameters (ΔMean, ΔSTD) was used by the authors to assess the degree of matching the given clustering method and metric in terms of the possibility of identifying particular PD forms.

The obtained results of comparing the quantity of Class 1 elements at the level of ΔMean = 0.0963 and ΔSTD = 0.057 in the case of component X, and ΔMean = 0 and ΔSTD = 0 in the case of component Y demonstrate a relatively accurate reconstruction of the original distribution of Class 1 elements by way

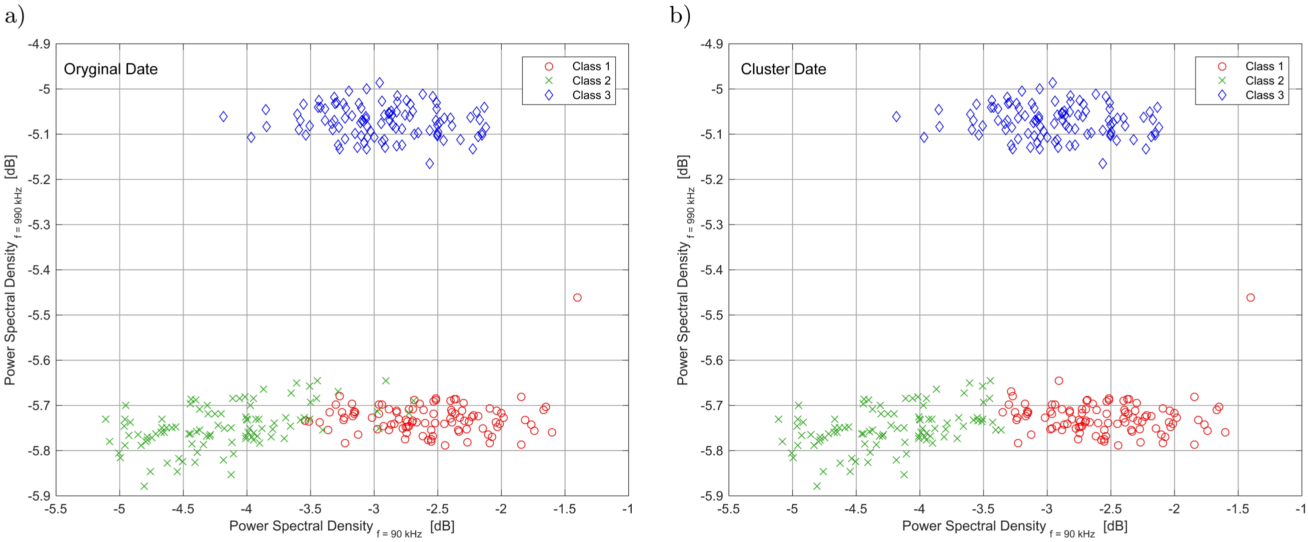

Fig. 2. Exemplary distribution of measurement data of AE signals from three PD forms for two selected PSD frequencies: a) original measurement data, b) data after clustering using the Ward and standardised Euclidean metric methods.

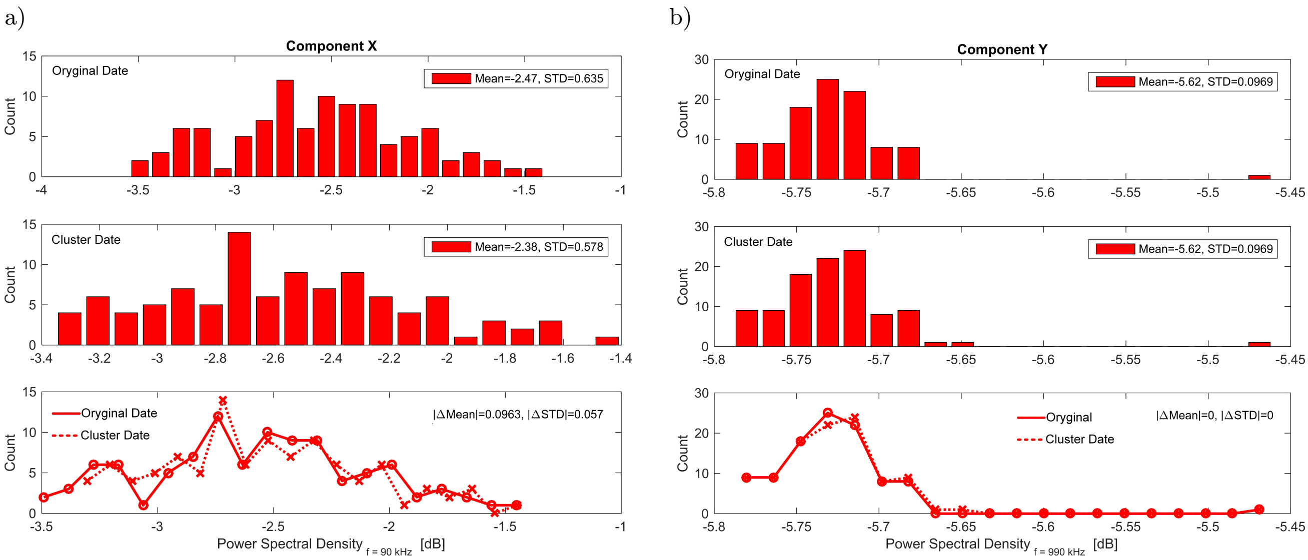

Fig. 3. Comparison of the quantity of Class 1 elements for the original measurement data distribution and the distribution obtained by way of clustering using the Ward and standardised Euclidean metric methods: a) PSD parameter's frequency component X, b) PSD parameter's frequency component Y.

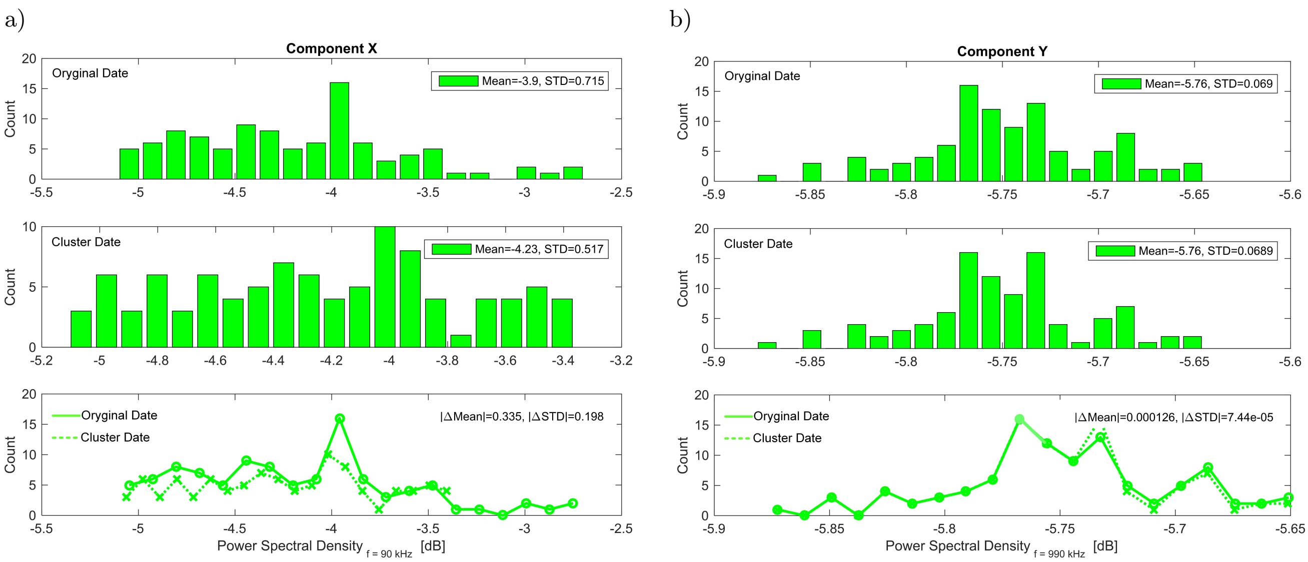

Fig. 4. Comparison of the quantity of Class 2 elements for the original measurement data distribution and the distribution obtained by way of clustering using the Ward and standardised Euclidean metric methods: a) PSD parameter's frequency component X, b) PSD parameter's frequency component Y.

of clustering using the Ward and standardised Euclidean metric methods.

The comparison of the quantity of Class 2 elements provided results at the level of ΔMean $= 0.335$ and ΔSTD $= 0.198$ in the case of component X, and ΔMean $= 0.000126$ and ΔSTD $= 0.00000744$ in the case of component Y. The results are slightly worse than in the case of Class 1 (Fig. 3), but similarly demonstrate a relatively accurate reconstruction of the original distribution of Class 2 elements by way of clustering.

In the case of Class 3, the result was the full reconstruction of the original distribution of measurement data of AE signals from the PD's by way of clustering. This is confirmed by the zero values of the results of ΔMean and ΔSTD differences, both for the PSD's component X and Y. The full reconstruction of the original distribution of Class 3 elements results from the clear separation of particular PSD frequency components of the AE signal for this PD form from the elements of the other defined classes.

The conducted research experiment featured analogous analyses for all clustering methods and metrics specified in Sec. 3. The results obtained this way, especially the ΔMean and ΔSTD parameters, are presented in Tables 1–6.

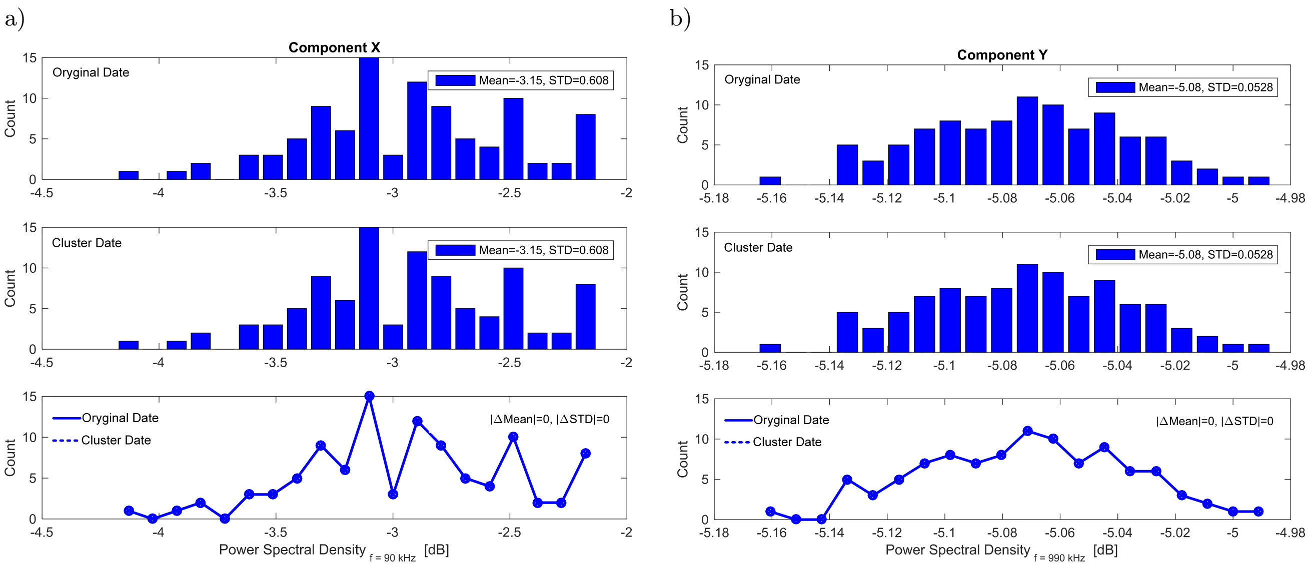

Fig. 5. Comparison of the quantity of Class 3 elements for the original measurement data distribution and the distribution obtained by way of clustering using the Ward and standardised Euclidean metric methods: a) PSD parameter's frequency component X, b) PSD parameter's frequency component Y.

Table 1. Results of clustering using various methods of Class 1 elements and the standardised Euclidean metric.

No.	Clustering method	ΔMean		ΔSTD	
		Component X	Component Y	Component X	Component Y
1.	Single	0.5730	0.3360	5.2800	5.2800
2.	Complete	0.0546	0.0000	0.0323	0.0000
3.	Average	0.0546	0.0000	0.0323	0.0000
4.	Centroid	0.0546	0.0000	0.0323	0.0000
5.	Ward	0.0963	0.0000	0.0570	0.0000

Table 2. Results of clustering using various metrics of Class 1 and the Ward method.

No.	Metric	ΔMean		ΔSTD	
		Component X	Component Y	Component X	Component Y
1.	Euclidean	0.1230	0.0000	0.0728	0.0000
2.	Seuclidean	0.0963	0.0000	0.0570	0.0000
3.	Cityblock	0.0546	0.0000	0.0323	0.0000
4.	Mahalanobis	0.2630	0.0000	0.1560	0.0000
5.	Minkowski	0.1230	0.0000	0.0728	0.0000

Table 3. Results of clustering using various methods of Class 2 elements and the standardised Euclidean metric.

No.	Clustering method	ΔMean		ΔSTD	
		Component X	Component Y	Component X	Component Y
1.	Single	0.5450	0.0000	0.3220	0.0000
2.	Complete	0.4850	0.0098	0.2870	0.0085
3.	Average	0.4850	0.0098	0.2870	0.0085
4.	Centroid	0.4850	0.0098	0.2870	0.0085
5.	Ward	0.3350	0.0001	0.1980	0.0000

Table 4. Results of clustering using various metrics of Class 2 and the Ward method.

No.	Metric	ΔMean		ΔSTD	
		Component X	Component Y	Component X	Component Y
1.	Euclidean	0.5910	0.0098	0.3500	0.0058
2.	Seuclidean	0.3350	0.0001	0.1980	0.0000
3.	Cityblock	0.4850	0.0098	0.2870	0.0085
4.	Mahalanobis	0.2170	0.0001	0.1280	0.0001
5.	Minkowski	0.5910	0.0098	0.3500	0.0058

Table 5. Results of clustering using various methods of Class 3 elements and the standardised Euclidean metric.

No.	Clustering method	Δ Mean		ΔSTD	
		Component X	Component Y	Component X	Component Y
1	Single	0.0000	0.0000	0.0000	0.0000
2	Complete	0.0000	0.0000	0.0000	0.0000
3	Average	0.0000	0.0000	0.0000	0.0000
4	Centroid	0.0000	0.0000	0.0000	0.0000
5	Ward	0.0000	0.0000	0.0000	0.0000

Table 6. Results of clustering using various metrics of Class 3 and the Ward method.

No.	Metric	ΔMean		ΔSTD	
		Component X	Component Y	Component X	Component Y
1.	Euclidean	0.0000	0.3040	0.0000	0.1800
2.	Seuclidean	0.0000	0.0000	0.0000	0.0000
3.	Cityblock	0.0000	0.0000	0.0000	0.0000
4.	Mahalanobis	0.0000	0.0000	0.0000	0.0000
5.	Minkowski	0.0000	0.3040	0.0000	0.1800

In the case of Class 1 elements, when using the similarity function (metric) in the form of standardised Euclidean distance, three clustering methods – complete linkage, average linkage and centroid linkage – gave the same effect. Slightly worse results were obtained in the case of the Ward linkage method, whereas the largest discrepancies between the original data distribution and the distribution obtained by way of clustering were obtained in the case of the single linkage method.

The most effective metric for Class 1 elements, using the Ward linkage clustering method, turned out to be the so-called Cityblock metric. Slightly worse results were obtained for the so-called Seuclidean, i.e. standardised Euclidean metric, whereas for the other three tested similarity functions, the obtained ΔMean and ΔSTD values are characterised by a higher value by nearly an order (for the PSD's frequency component X).

Similarly, as in the case of Class 1 elements, the use for Class 2 elements of the metric of standardised Euclidean distance has given the same effect for three clustering methods – complete linkage, average linkage and centroid linkage. The best clustering results were obtained however for the Ward linkage method. The largest discrepancies between the original data distribution and the distribution obtained by way of clustering, similarly as in the case of Class 1, were obtained for the single linkage method. These discrepancies are however smaller than in the case of clustering of the Class 1 elements.

Based on the conducted testing, it was concluded that the most effective similarity function for Class 2 elements, using the Ward linkage clustering method, is the Mahalanobis metric, also referred to as the so-called Euclidean distance. Slightly worse results were obtained for the Seuclidean and Cityblock metrics. The worst results were obtained for the Euclidean and Minkowski probability functions.

In the case of Class 3 elements, for which the original distribution of the measurement data was characterised by a clear deviation from the other two analysed Classes, the selection of the clustering method had no impact on the obtained ΔMean value and ΔSTD parameters (Table 5). The value of the determined parameters amounted to zero for each of the applied and tested clustering methods. However, based on the assessment of the change in the similarity function for Class 3 elements, using the Ward linkage clustering method, it was concluded that the most effective metrics for this clustering method are the Euclidean and Minkowski functions.

5. Conclusion

The results presented in this article concerning the use of clustering for analysing and classifying AE signals, confirm the possibility of using this method to identify the basic PD forms occurring in the transformer's oil-paper insulation system. Based on the conducted testing, it was proven that the use of various clustering methods and similarity functions (metrics) allowed reconstructing, with substantial degree of accuracy, the original distribution of measurement data of the AE signals, deriving from the three modelled PD forms. It is, however, necessary to note that the effective identification of particular PD forms based on the AE signal analyses and the clustering methods discussed in the article is also largely dependent on the correct selection of the recorded signal's PSD frequency components X and Y. As part of this article, two selected PSD streak frequencies were adopted for the experiment. Currently, the team is conducting further testing aimed at minimising the determined ΔMean and ΔSTD indicators, amongst others, by changing the frequencies of components X and Y of the determined PSD.

An important feature of the method of identifying the basic PD forms proposed in this article is the possibility of further optimisation and selection of the most effective clustering methods and metrics, and therefore the possibility of more accurate reconstruction of the original measurement data by using numerical indicators, which include the difference of the ΔMean and ΔgSTD values. In the authors' opinion, thanks to the possibility of further optimisation, the methodology presented in the article can be more reliable and effective in identifying damage occurring in oil-paper insulation systems of PD transformers.

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