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THE APPLICATION OF THE RESILENT BACKPROPAGATION ALGORITHM AND POWER SPECTRUM DENSITY FOR RECOGNIZING THE ACOUSTIC EMISSION SIGNALS GENERETED BY BASIC PARTIAL DISCHARGE FORMS USING ARTIFICIAL NEURON NETWORKS

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The subject matter of this paper refers to the correct recognition of the acoustic emission (AE) signals generated by basic partial discharge forms (PDs). The paper presents research results of the application of unidirectional artificial neural networks (ANN) for recognizing basic PD forms that can occur in paper-oil insulation impaired by aging processes. The research work results present recognition effectiveness of basic PD forms depending on the number of basic forms passed simultaneously onto the network inputs and the size of the teaching sequence. Power spectrum density was assumed as the parameter of the AE signal generated by the assumed PD forms. The paper also presents the results of the network effectiveness analysis depending on the number of the points averaging the power spectrum density, the number of neurons of the concealed layer and the size of the teaching sequence.

Key words: partial discharge, acoustic emission method, artificial neural network, paper-oil insulation system.

1. Introduction

The many-year research work referring to the issues connected with diagnostics of power appliances led to the elaboration of modern methods that enable a correct evaluation of their technical condition, which refers mainly to the endurance of insulation systems. At present there exist a few methods that make the detection of PDs possible, the presence and development of which is connected with a gradual degradation of a paper-oil insulation system. The acoustic method, which has been developed intensively in recent years and which makes PD detection and location during a regular transformer operation possible [9], is one of such methods. The AE signals generated by PDs characterize with wide waveband and their range belongs to compartment (20÷700) kHz. In the face of this applied measuring apparatus possessed the same range of transfer band.

The registered AE signals generated by PDs can be strictly connected with basic PD forms presented in literature [1, 2], and the particular PD forms can be identified with the type and degree of paper-oil insulation damage. Therefore, thanks to the correct recognition process of the AE signals registered it is possible to identify the type of the insulation system damage and to perform initial evaluation of the degradation degree of the insulation under study.

Based on literature and our own research work, the results of which are presented, among others, in [1–4], referring to bringing into relationship basic PD forms with actual damage that can occur in paper-oil insulation of power transformers, the authors of the research work conducted distinguished the following PD types:

- discharges in the point-point system in oil, which can model PDs that occurred due to insulation damage of two neighboring windings of the transformer winding,
- discharges in the point-point system in oil with gas bubbles, which can model PDs in gassy oil and are caused by insulation damage of two neighboring transformer windings,
- discharges in the point-plane system in oil, which can model PDs in occurring between a damaged part of a transformer winding insulation and grounded flat parts (elements of the tub),
- discharges in the surface system of two flat electrodes with paper-oil insulation between them; the most common PD form occurring in the so-called triple point, in which the electrode surface touches solid and liquid dielectrics,
- discharges in the surface system of one flat electrode and the other multipoint electrode with paper-oil insulation between them; different distribution of the electric field intensity compared with discharges in the surface system with two flat electrodes,
- discharges in the multipoint-plane system in oil, which can model PDs occurring between a multipoint insulation damage of a transformer winding and grounded flat parts (elements of the tub),
- discharges in the multipoint-plane system in oil with gas bubbles, which can model PDs occurring between a multipoint insulation damage of a transformer winding and grounded flat parts (elements of the tub), but in oil with gas particles,
- discharges on particles of an indefinite potential that move in oil, which can model PDs occurring in oil containing particles of cellulose fibres formed in the process of a gradual degradation of paper-oil insulation caused by aging processes.

2. Characteristics of the neuron classifier used and its teaching algorithm

The authors of this paper suggested the use of ANN for recognition of the particular insulation system defects based on the AE signal analysis generated by PD forms assumed for the research purposes. The application of the neuron classifier involving parallel data processing constitutes a significant acceleration of the recognition and classification process and in relation to the methodology, which has been used so far and has been based on comparing graphic representation of the selected parameters of the AE signals, and it is characteristic of a much more effective interpretation of the measuring signals registered. Based on literature on the application of ANNs as tools recognizing and classifying models [5–8], the application of a unidirectional multilayer neural network was suggested for tasks connected with recognizing the registered AE signals generated by basic PD forms. Matlab software environment, mainly the Neural Network Toolbox packet, was used for ANN implementation, teaching and testing. The structure applied is a network of Feed–Forward Backpropagation Network (F–F BP) type, in which each neuron has a sigmoid activation function. The structure adopted for the research purposes had three layers: an input layer, one concealed layer, and an output layer. The teaching process of the network applied was carried out based on supervised teaching (with a teacher), thus some of the measuring files containing information on the AE signals from PDs were treated as vectors of a teaching sequence (CU), and the others as vectors of a test sequence (CT). For each basic PD form under study a hundred measuring files were registered, out of which the representatives of the CU were selected randomly. The remaining part of the population of the AE signals measured was used for testing the degree of the network training in respect to the recognition effectiveness of the particular PD forms. The frequency analysis results of the registered AE signals generated by basic PD forms – power spectrum density (PSD) – were suggested as CU and CT parameters during teaching and testing the ANN. The correction process of the particular neuron weights that entered into the composition of the network was based on one of the varieties of backpropagation strategy – Resilient Backpropagation (RPROP) algorithm, described by the dependence:

$$w_{ij}^{(k)}(n+1) = w_{ij}^{(k)}(n) - \eta_{ij}^{(k)}(n)\,\mathrm{sgn}\Big(\nabla_{ij}^{(k)}(n)\Big)\,, \tag{1}$$

where $\eta_{ij}^{(k)}$ – individual teaching coefficient for each weight, $\nabla_{ij}^{(k)}(n)$ – error function gradient component.

The eaching coefficient is selected individually in each cycle for each weight w_{ij} based on the gradient value changes. If in both consecutive iterations the gradient sign is the same, the increase of teaching coefficient η takes place, and if not, its reduction takes place:

$$\eta_{ij}^{(k)}(n) = \begin{cases} \min\Big(a\eta_{ij}^{(k)}(n-1),\ \eta_{\max}\Big) & \text{for} \quad \nabla_{ij}^{(k)}(n)\,\nabla_{ij}^{(k)}(n-1) > 0, \\ \max\Big(b\eta_{ij}^{(k)}(n-1),\ \eta_{\min}\Big) & \text{for} \quad \nabla_{ij}^{(k)}(n)\,\nabla_{ij}^{(k)}(n-1) < 0, \\ \eta_{ij}^{(k)}(n-1) & \text{in} \quad \text{the other case.} \end{cases} \tag{2}$$

Values a and b are constants ($a = 1.2$; $b = 0.5$), $\eta_{\max}$ and $\eta_{\min}$ denote maximum and minimum values of the teaching coefficient ($\eta_{\max} = 50$; $\eta_{\min} = 10^{-6}$), and sgn function denotes an argument sign [7, 8].

3. Evaluation of recognition effectiveness of basic PD forms by ANNs using power spectrum density and Resilent Backpropagation

In order to determine the recognition effectiveness of the PD forms assumed by the network created, the concept of a “class” was introduced, which, in this case, specifies the PD forms assumed. Adopting for the analysis eight PD forms, the following classes were defined: class 1 – discharges in the point-point system in oil, class 2 – discharges in the point-point system in oil with gas bubbles etc.

Figure 1 shows the results of total recognition effectiveness of the eight PD forms (eight classes) in dependence on the size of the teaching sequence (RCU – *STS*) and the number of power spectrum density averaging points recognizable (LPU). The aim of the research work conducted was determining the minimum value of PSD averaging points which make an unmistakable characterization and recognition of the particular PD forms based on the parameters of their AE signal frequency analysis possible. The number of neurons of the concealed layer (LNWU) was assumed as a constant parameter of the analysis.

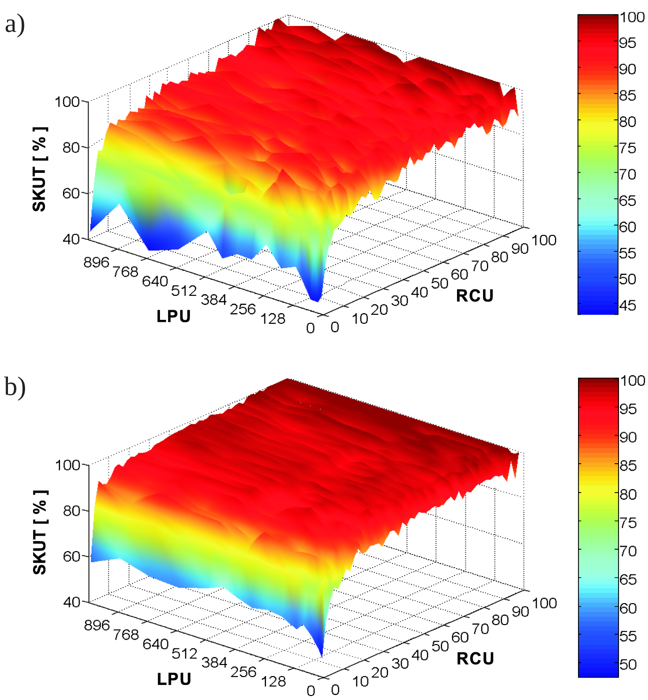
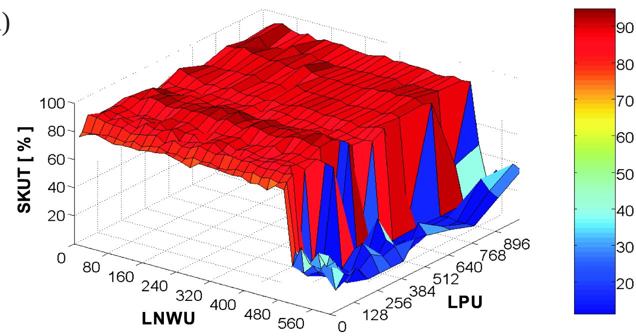


Fig. 1. Total recognition effectiveness of the eight PD forms (SKUT) by the ANN applied in dependence on CU size (RCU) and the changing number of PSD averaging points (LPU): a) $\mathrm{LNWU} = 5$, b) $\mathrm{LNWU} = 45$.

It results from the characteristics shown in Fig. 1 that in order to achieve a satisfying recognition effectiveness (above 90%) for eight classes passed simultaneously on the ANN input layer it is enough to have about 128 PSD averaging points. The research work carried out also proved that increasing LPU over 128 points insignificantly increases recognition effectiveness but causes a significant extension of the teaching process and the recognition of the PD forms under study. From graphic analysis of the data obtained it also results that RCU, the value of which should be at least 30 to obtain SKUT $\geq 90\%$, plays a significant role in recognition effectiveness values obtained. The consecutive characteristics show the dependence of LNWU on the total recognition effectiveness of basic PD forms assumed in this paper.

Based on the results shown in Fig. 2, it can be again observed that in order to ensure recognition effectiveness of basic PD forms it is necessary to assume LPU at the level of at least 128 points. It was observed, analyzing the characteristics in respect of the influence of the number of concealed neurons on the recognition effectiveness obtained, that the optimum LNWU value is number 45. A smaller number of neurons causes obtaining lower effectiveness values (lower than 90%), and LNWU increase above this value significantly increases the process of training and testing of the architecture adopted, at an insignificant improvement of recognition effectiveness (0.5–1%). The results presented in Fig. 2 also confirmed the influence of RCU on the effectiveness results obtained, as the change of the teaching sequence size from $\mathrm{RCU} = 10$ (Fig. 2a) to $\mathrm{RCU} = 40$ (Fig. 2b) caused the recognition effectiveness improvement from about 85% to about

a)



b)

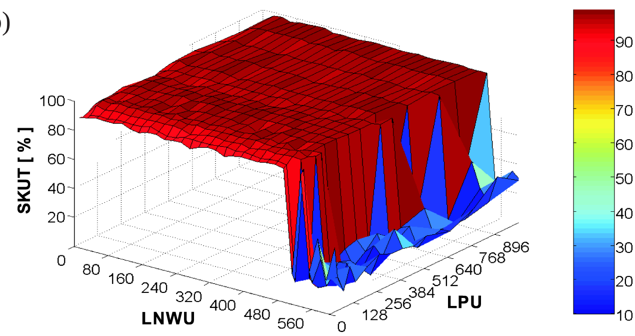


Fig. 2. Total recognition effectiveness of the eight PD forms (SKUT) by the ANN applied in dependence on the number of neurons in the concealed layer (LNWU) and a changing number of PSD averaging points (LPU): a) $\mathrm{RCU} = 10$, b) $\mathrm{RCU} = 40$.

97%. It results from the dependences shown in Figs. 2a and 2b that for a certain LNWU value there exists such a point after exceeding of which there occurs a sudden drop in recognition effectiveness of the particular PD forms by the network. It happens so because while increasing LNWU there takes place a gradual saturation of the particular neuron weights in the network and the so-called ANN learning “by heart”.

Based on the above-presented research results, determining the possibility of using PSD and RPROP algorithm for recognizing basic PD forms by the network, PSD determined for $\mathrm{LPU} = 128$ was adopted as a parameter of the AE signal generated by the particular PD forms.

It results from the dependence (Figs. 3a, 3b) of recognition effectiveness of the particular PD forms on the number of recognizable classes (LKR) and RCU at a constant number of the concealed layer neurons that with the increase of the number of recognizable classes and a constant RCU value the recognition effectiveness of the network tested decreases. This dependence can be seen most clearly in Fig. 3a, in which the structure of the concealed layer contains 5 neurons. In this case the effectiveness improvement can be achieved by increasing RCU. This effectiveness, however, is not sufficient from the point of the recognition correctness of the particular PD form as it

a)

b)

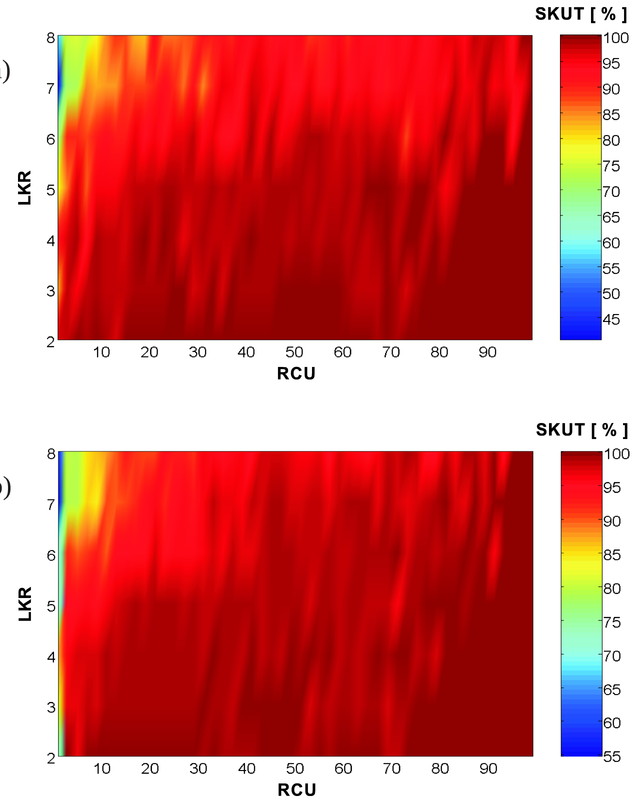


Fig. 3. Recognition effectiveness of the adopted PD forms (SKUT) by the ANN applied in dependence on the CU size (RCU) and a changing number of recognizable classes (LKR): a) $\mathrm{LNWU} = 5$, b) $\mathrm{LNWU} = 45$.

does not exceed 90%. Increasing the number of the concealed layer neurons, which is shown in Fig. 3b, is another measure improving recognition effectiveness of the forms under study.

4. Summing-up

The research work carried out, connected with the evaluation of ANN for the analysis of the AE signals and their recognition based on basic PD forms, confirms the existence of such a possibility. The adopted type of the neural network F-F BP of a three-layer structure enables, to a great extent, recognition of the particular PD forms. The adoption of RPROP algorithm as a teaching strategy makes it possible to maintain a considerable stability of the ANN training process. Additionally, this algorithm is characteristic of a considerable processing speed of the data stored, which is confirmed, among others, by the recognition effectiveness results of the registered AE signals coming from PDs generated, presented in this paper. The research work carried out also proved the PSD usefulness, the parameter representing the AE signal, as a criterion of teaching and testing the neural network applied. In order to achieve recognition effectiveness of the particular PD forms by the adopted neuron classifier at the level exceeding 90% $(\mathrm{LKR} = 8)$ in optimum time possible, the number of the concealed layer neurons should be $\mathrm{LNWU} = 45$, and the teaching sequence size (RCU) should belong to the range from 30 to 50.

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