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DEVELOPMENT OF FUZZY NEURAL NETWORK FOR THE INTERPRETATION OF THE RESULTS OF DISSOLVED IN OIL GASES ANALYSIS

Purpose. The purpose of this paper is a diagnosis of power transformers on the basis of the results of the analysis of gases dissolved in oil. Methodology. To solve this problem a fuzzy neural network has been developed, tested and trained. Results. The analysis of neural network to recognize the possibility of developing defects at an early stage of their development, or growth of gas concentrations in the healthy transformers, made after the emergency actions on the part of electric networks is made. It has been established greatest difficulty in making a diagnosis on the criterion of the boundary gas concentrations, are the results of DGA obtained for the healthy transformers in which the concentration of gases dissolved in oil exceed their limit values, as well as defective transformers at an early stage development defects. The analysis showed that the accuracy of recognition of fuzzy neural networks has its limitations, which are determined by the peculiarities of the DGA method, used diagnostic features and the selected decision rule. Originality. Unlike similar studies in the training of the neural network, the membership functions of linguistic terms were chosen taking into account the functions gas concentrations density distribution transformers with various diagnoses, allowing to consider a particular gas content of oils that are typical of a leaky transformer, and the operating conditions of the equipment. Practical value. Developed fuzzy neural network allows to perform diagnostics of power transformers on the basis of the result of the analysis of gases dissolved in oil, with a high level of reliability. References 16, tables 3, figures 9.

Key words: **diagnostics of transformers, analysis of dissolved gases in oil, peculiarities of gas content, concentration levels, fuzzy neural networks, membership function, Weibull distribution, network training, fuzzy conclusion, wrong decisions.**

Разработана и обучена нечеткая нейронная сеть для интерпретации результатов хроматографического анализа растворенных в масле газов. Предложено определять функции принадлежности лингвистических термов с учетом функций плотностей распределения концентраций газов для трансформаторов с различным состоянием. Выполнено тестирование обученной сети на независимой выборке. Проанализированы возможности нейронных сетей распознавать развивающиеся дефекты на ранней стадии их развития, или рост концентраций газов в исправных трансформаторах, после аварийных воздействий со стороны электрических сетей. Библ. 16, табл. 3, рис. 9.

Ключевые слова: **диагностика трансформаторов, анализ растворенных в масле газов, особенности газосодержания, уровни концентраций, нечеткие нейронные сети, функции принадлежности, распределение Вейбулла, обучение сети, нечеткий вывод, ошибочные решения.**

Introduction. One of the ways to increase the operational reliability of high-voltage electric power equipment especially that operated outside the normative service life is to improve existing methods and means of monitoring for obtaining diagnostic information, development of mathematical models and algorithms for assessing the technical condition of electrical equipment. The most promising, according to the authors, the direction of such an improvement is the development of computer systems for technical diagnostics using the apparatus of fuzzy logic and neural networks, which can provide an increase in the reliability of recognition and prediction of the technical condition and resource of the object.

Analysis of publications. At present, the mathematical apparatus of fuzzy logic and neural networks is widely used to detect developing defects and to recognize their type both by domestic [1-6] and foreign [7-11] researchers. In most of the published works, international, national or departmental standards or techniques for interpreting the results of chromatographic analysis of dissolved gases in oil (CADG) are used as a decisive rule. When using the fuzzy logic device, the membership function type as well as their numerical characteristics, are determined based on expert estimates or from existing standards. As a rule, when learning and testing the developed systems of fuzzy inference or neural networks, either the results of the CADG are used, corresponding to the working or defective condition of the equipment. But at the same time, the peculiarities of the gas content of oils in serviceable transformers were not taken into account, which are determined by the features of the design, operating conditions and a number of other factors. In addition, despite a rather large number of publications on the use of neural networks to interpret the results of CADG, a number of issues remain uninformed. In particular, issues related to the ability of neural networks to recognize developing defects at an early stage of their development, or the growth of gas concentrations in serviceable transformers, after emergency actions on the part of electrical networks, have not been considered. The latter circumstances served as an excuse for writing this paper.

The goal of the work is the development, training and testing of fuzzy neural network, for diagnostics of power transformers based on the results of CADG, and also analysis of the possibility of this network to recognize developing defects at an early stage of their development and growth of gas concentrations in serviceable transformers as a result of external influences.

Initial data for the network training. To train the network, the results of CADG were used in Donetsk, Luhansk, Sumy and Kharkiv regions, Ukraine. In total, the results of observations of 426 transformers with voltage of 110 and 330 kV, an unpressurized version, were analyzed. Analyzed transformers differ both in voltage class, and in nominal power, and in design, and most importantly – in terms of operation, i.e. by the values of the load, by the frequency and level of action of short-circuit currents, by the multiplicity of the effects of overvoltages, etc. All this leads to the fact that the values of gas concentrations vary in a fairly wide range of values. For the convenience of analysis, the values of the gas concentrations were the concentration levels recommended in [12] were used to diagnose the state of high voltage equipment with voltages up to 330 kV. Values of gas concentrations corresponding to different levels are given in Table 1. According to [12], if the values of the gas concentrations correspond to level 1, this indicates a normal, defect-free state of the equipment. If the concentration of at least one of the gases corresponds to level 2, then the decision on the state of the equipment is taken based on the analysis of the values of the rates of increase in the sum of the hydrocarbon series gases (the defect is considered «present» if this rate exceeds 30 ml/day). If the concentration of at least one of the gases corresponds to level 3, then the presence of a defect without taking into account the rate of increase in gas concentrations is predicted.

Table 1

Levels of the state of oil-filled equipment by values of gas concentrations

Concentration level	Gases dissolved in oil				
	H_2	CH_4	C_2H_6	C_2H_4	C_2H_2
1	<0.01	<0.005	<0.005	<0.0015	<0.00005
2	0.01-0.015	0.005-0.012	0.005-0.01	0.0015-0.01	0.00005-0.001
3	>0.015	>0.012	>0.005	>0.0015	>0.001

The performed analysis showed that out of 7393 results of measurements of hydrogen concentrations 5161 (H_2) the value or 69.81% did not exceed the detection limit of the chromatograph. Another 2106 values (28.49%) of concentrations did not exceed the value of the analytical recognition threshold (0.005% by vol.) regulated in [12]. Only 71 values (0.96%) corresponded to level 1 (less than 0.01% by vol.). Level 2 (0.01-0.015% by vol.) corresponded to 26 values (0.35%), and to level 3 (more than 0.015% by vol.) – 29 values (0.39%).

The concentrations of methane (CH_4) below the detection limit by the chromatograph were found in 2,304 oil samples, which is 31.6% of all observations for this gas; another 3,342 (45.2%) concentrations of methane were below the analytical recognition threshold (0.0015% by vol.). 1160 values (15.69 %) corresponded to level 1 (up to 0.005% by vol.), level 2 (0.005-0.012% by vol.) – 367 values (4.96%), and to level 3 (more than 0.012) – 220 values (2.98%).

The ethane concentrations (C_2H_6) do not exceed the detection limit of the chromatograph in 1957 samples (26.47%), in 4485 oil samples (60.67%), the ethane concentrations did not exceed the analytical recognition threshold (0.0015% by vol.). 619 concentrations (8.37%) corresponded to level 1 (up to 0.005% by vol.), level 2 (0.005-0.01% by vol.) – 153 values (4.96%), and level 3 (more than 0.01 % by vol.) – 179 values (2.42%).

Of the 7393 ethylene concentrations (C_2H_4), 1090 values (14.74%), 3763 (50.90%) were found below the detection limit by the chromatograph, did not exceed the analytical recognition threshold (which is 0.0015% by vol.). It should be noted that for ethylene, the values of the analytical recognition level coincide with the value of the upper limit of level 1. Therefore, in the future for ethylene, all values corresponding to level 1 are assigned to values not exceeding the analytical recognition threshold. In 1914 samples, the values of ethylene concentrations (25.89%) correspond to level 2 (0.0015-0.01% by vol.), And 626 ethylene values (8.47%) correspond to level 3 (more than 0.01% by vol.).

The concentrations of acetylene (C_2H_2) not exceeding the detection limit by the chromatograph were found in 4551 oil samples, which is 61.56% of all observations for this gas. Another 1602 values (21.67%) of acetylene concentrations were below the analytical recognition threshold. Due to the fact that for acetylene the recognition level (0.0003% by vol.) exceeds the upper limit of level 1 (0.00005% by vol.) acetylene values with concentrations above the analytical recognition threshold, but below level 3 are assigned to level 2 (from 0.00005 to 0.001% by vol.). Level 2 corresponded to 982 values (13.28%), and to level 3 (more than by 0.001% by vol.) – 258 values (3.49%).

Thus, on the basis of the analysis, it is established that, in serviceable transformers of a leaky design, gas concentrations, upper limit values of level 2, can be exceeded, which can be interpreted as a defect. The greatest probability of exceeding the boundary value of level 2 was found in ethylene, then acetylene, methane, ethane and least of all hydrogen.

At the same time, the greatest probability of realization of gas concentrations below the analytical detection threshold is hydrogen, then acetylene, ethane and methane. For ethylene, this probability is the lowest. The maximum number of values with concentrations above the analytical recognition threshold is C_2H_4 (2540 values or 34.36%). Then follows CH_4 (1747 values or 23.63%), then C_2H_2 (1240 values or 16.77%). The lowest values with concentrations above the analytical detection threshold were found in C_2H_6 (951 or 12.86%) and H2 (126 values or 1.70%).

The received results allow to draw a conclusion that in serviceable transformers, the concentration values can correspond to the values characteristic for the defective state (level 3). As shown by the analysis performed in [13, 14], one of the main reasons for exceeding the gas concentrations of boundary values, fault-free transformers are emergency actions from electrical networks (short circuits, overvoltages, overloads, etc.).

To train the neural network, the results of CADG were used for defective equipment, which were obtained both as a result of cooperation of authors with Ukrainian energy companies, and from open domestic and foreign literary sources. The total amount of sampling values was 1103 measurements. The distribution of sample values by types of defects is given In Table 2. As can be seen from the table in the sample presented to the analysis, different types of defect have a different volume of sample values, i.e. Different probability of their occurrence. The greatest number of defects is due to overheating in the temperature range above 700 °C (in the Table is designated as superheating of high temperatures) and overheating in the high temperature region, which are accompanied by electric discharges. The lowest number of observations is for electric discharges of low energy and overheating, which turn into an arc discharge. The performed analysis showed that in defective equipment, the values of gas concentrations substantially depend on the stage of defect development, while in the initial stages the concentration values may not exceed the boundary values corresponding to level 3 [12], but as the defect develops, the values of the concentrations increase. Another important factor affecting the values of the concentrations of individual gases is the type of defect. As a rule, the maximum values of concentrations are observed in gases characteristic for this type of defects. For concomitant gases, the concentrations are somewhat less. At the same time, the values of the concentrations of gases that are not characteristic for this type of defect have values corresponding to either levels 1 or 2, or they do not exceed the detection limit of the chromatograph.

Table 2

Distribution of sample values by types of defects

No.	Defect type	Scope of the sample
1	Partial discharge	115
2	Partial discharges of high intensity	15
3	Spark and creeping discharges	81
4	Low-energy discharges	17
5	Arc discharge (H_2)	67
6	Arc discharge (C_2H_2)	43
7	Discharges of high energy (C_2H_2)	53
8	Overheating of low temperatures (CH_4)	48
9	Overheating of low temperatures (C_2H_6)	57
10	Overheating of average temperatures (CH_4)	68
11	Overheating of average temperatures (C_2H_4)	81
12	Overheating of high temperatures (C_2H_4)	260
13	Overheating of low temperatures and discharges	35
14	Overheating in the arc (CH_4)	16
15	Overheating transitions into discharges (C_2H_6)	27
16	Overheating of high temperatures and discharges	120

Note: the gas with the maximum concentration is shown in brackets.

Each result of measurements of gas concentrations was assigned a code corresponding to the concentration levels from Table 1. The coding of transformer diagnoses is given in Table 3.

Table 3

The coding of transformer diagnoses

Code	Diagnosis
1	Working condition
2	Suspicious condition
3	Defective condition

Fuzzy neural network training. Next, a fuzzy neural network topology was developed, which is shown in Fig. 1. The created network has 15 inputs, three inputs for each of the gases. The number of learning cycles created by the fuzzy neural network was 300 epochs.

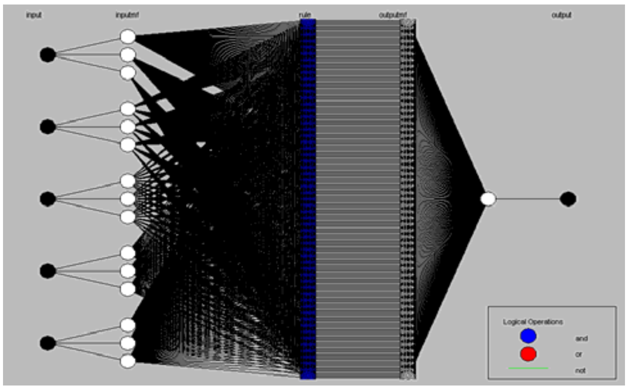


Fig. 1. Fuzzy neural network topology

Fig. 2 shows the dependence of the learning error on the number of training cycles.

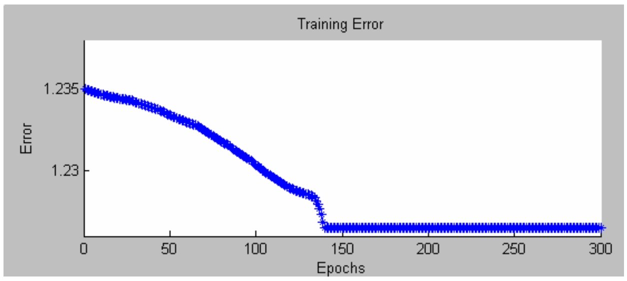


Fig 2. Dependence of the learning error of a fuzzy neural network on the number of training cycles

As can be seen from Fig. 2, the decrease in the learning error is observed approximately to the middle of the training interval. Further increase in the number of training cycles does not lead to an increase in the reliability of recognition. To reduce the error, the fuzzy logic apparatus was used.

Stage of fuzzification. At this stage, the input linguistic variables were identified:

LV_{inp1}: <hydrogen concentration>
LV_{inp2}: <methane concentration>
LV_{inp3}: <ethane concentration>
LV_{inp4}: <ethylene concentration>
LV_{inp5}: <acetylene concentration>

Further, LV_{inpi} is divided into several linguistic terms LT_{ij} characterizing the peculiarities of the state of a given variable:

$$LT_{ij}, j=1\ldots n,$$

where: j is the number of term LV_{inpi}, n is the number of terms into which LV_{inpi} is divided.

The dividing into term for each of the gases was the following:

LV_{inp1} is divided into three LT
- LT_{11}: < concentration within normal limits – **1**>
- LT_{12}: < suspicious concentration – **2**>
- LT_{13}: < defective concentration – **3**>

LV_{inp2} is divided into three LT
- LT_{21}: < concentration within normal limits – **1**>
- LT_{22}: < suspicious concentration – **2**>
- LT_{23}: < defective concentration – **3**>

LV_{inp3} is divided into three LT
- LT_{31}: < concentration within normal limits – **1**>
- LT_{32}: < suspicious concentration – **2**>
- LT_{33}: < defective concentration – **3**>

LV_{inp4} is divided into three LT
- LT_{41}: < concentration within normal limits – **1**>
- LT_{42}: < suspicious concentration – **2**>
- LT_{43}: < defective concentration – **3**>

LV_{inp5} is divided into three LT
- LT_{51}: < concentration within normal limits – **1**>
- LT_{52}: < suspicious concentration – **2**>
- LT_{53}: < defective concentration – **3**>

The definition of membership functions is quite a challenge. To ensure that the selected membership functions and their boundaries most adequately describe the results of chromatographic analysis, the functions of the density distribution of gas concentrations for serviceable and defective states were used [15]. As an example, Fig. 3, the Weibull theoretical density distributions are given for methane concentrations obtained for serviceable transformers (***D*₁**), serviceable transformers after emergency actions from electrical networks (***D*₁₂**) and transformers in which a defect (***D*₂**) is detected.

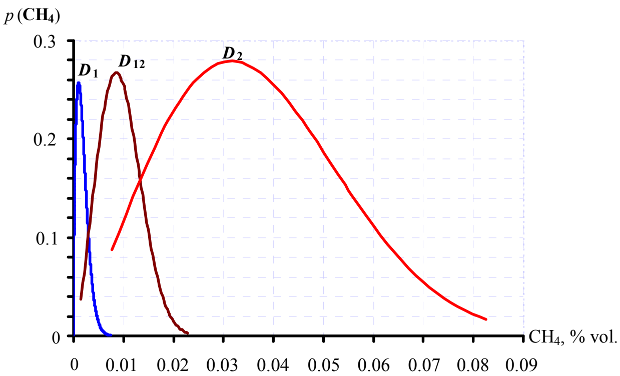


Fig. 3. Density of theoretical methane distributions for transformers with different state

As a membership function, it is very convenient to use a trapezoidal function, the degree of belonging to which has a maximum value in the middle of the interval and decreases along its edges. As borders for $\mathbf{LT_1}$ of all linguistic variables, the boundaries corresponding to the functions of the density distribution of gas concentrations were chosen for transformers with different states (see Fig. 3). The boundary values for $\mathbf{LT_2}$ and $\mathbf{LT_3}$ of all linguistic variables were chosen on the basis of the functions of the distribution densities. Fig. 4 shows the functions of methane for three linguistic terms. As can be seen from Fig. 4 membership functions are chosen in such a way as to take into account both the recommendations of СОУ-Н ЕЕ 46.501:2006, and the operational experience reflected in the form of density distribution functions.

Output linguistic variables have the form:

LV_{out1}: < Concentrations within normal limits – **1**>
LV_{out2}: < Concentrations above normal – **2**>
LV_{out3}: < The concentration values correspond to the presence of a defect – **3**>

The dividing into term was the following:

LV_{out1} is divided into two LT
- LT_{11}: <Corresponds – *Y*>
- LT_{12}: <Does not correspond – *N*>

LV_{out2} is divided into two LT
- LT_{21}: <Corresponds – *Y*>
- LT_{22}: <Does not correspond – *N*>

LV_{out3} is divided into two LT
- LT_{31}: <Corresponds – *Y*>
- LT_{32}: <Does not correspond – *N*>

As the membership functions for each of the terms, a triangular function was chosen.

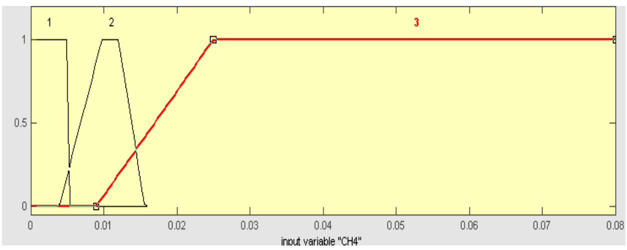


Fig. 4. The membership functions of three linguistic terms for, linguistic variable content of methane in oil

Stage of calculating the rule. A system with fuzzy logic should have a rules base, which, in essence, is the empirical knowledge of the expert about the control mechanism. To calculate the rules, the fuzzy inputs received from the fuzzification block and the rules in the knowledge base are used. In the left part of the rules, possible situations at the input of the system are sorted, and on the right-hand side it is indicated which LV describes the correct reaction of the system. As a decisive rule, the recognition technique was regulated in [9]. In short, the rules base can be represented in the form:

Rule 1: **IF** [$H_2\in1$] **AND** [$CH_4\in1$] **AND** [$C_2H_6\in1$] **AND** [$C_2H_4\in1$] **AND** [$C_2H_2\in1$] **THEN** [**D**$\in$ **1**];

Rule 2: **IF** [$H_2\in2$] **AND** [$CH_4\in1$] **AND** [$C_2H_6\in1$] **AND** [$C_2H_4\in1$] **AND** [$C_2H_2\in1$] **THEN** [**D**$\in$ **2**];

Rule 3: **IF** [$H_2\in1$] **AND** [$CH_4\in2$] **AND** [$C_2H_6\in1$] **AND** [$C_2H_4\in1$] **AND** [$C_2H_2\in1$] **THEN** [**D**$\in$ **2**];

…
Rule 6: **IF** [$H_2 \in 1$] **AND** [$CH_4 \in 1$] **AND** [$C_2H_6 \in 1$] **AND** [$C_2H_4 \in 1$] **AND** [$C_2H_2 \in 2$] **THEN** [**D**$\in$ **2**];
Rule 7: **IF** [$H_2 \in 2$] **AND** [$CH_4 \in 2$] **AND** [$C_2H_6 \in 1$] **AND** [$C_2H_4 \in 1$] **AND** [$C_2H_2 \in 1$] **THEN** [**D**$\in$ **2**];
…
Rule 17: **IF** [$H_2 \in 1$] **AND** [$CH_4 \in 1$] **AND** [$C_2H_6 \in 1$] **AND** [$C_2H_4 \in 2$] **AND** [$C_2H_2 \in 2$] **THEN** [**D**$\in$ **2**];
Rule 18: **IF** [$H_2 \in 2$] **AND** [$CH_4 \in 2$] **AND** [$C_2H_6 \in 2$] **AND** [$C_2H_4 \in 1$] **AND** [$C_2H_2 \in 1$] **THEN** [**D**$\in$ **2**];
…
Rule 27: **IF** [$H_2 \in 1$] **AND** [$CH_4 \in 1$] **AND** [$C_2H_6 \in 2$] **AND** [$C_2H_4 \in 2$] **AND** [$C_2H_2 \in 2$] **THEN** [**D**$\in$ **2**];
Rule 28: **IF** [$H_2 \in 2$] **AND** [$CH_4 \in 2$] **AND** [$C_2H_6 \in 2$] **AND** [$C_2H_4 \in 2$] **AND** [$C_2H_2 \in 1$] **THEN** [**D**$\in$ **2**];
…
…
Rule 48: **IF** [$H_2 \in 1$ **OR** $H_2 \in 2$] **AND** [$CH_4 \in 1$ **AND** $CH_4 \in 2$] **AND** [$C_2H_6 \in 1$ **OR** $C_2H_6 \in 2$] **AND** [$C_2H_4 \in 3$] **AND** [$C_2H_2 \in 3$] **THEN** [**D**$\in$ **3**];
Rule 49: **IF** [$H_2 \in 3$] **AND** [$CH_4 \in 3$] **AND** [$C_2H_6 \in 3$] **AND** [$C_2H_4 \in 1$ **OR** $C_2H_4 \in 2$] **AND** [$C_2H_2 \in 1$ **OR** $C_2H_2 \in 2$] **THEN** [**D**$\in$ **3**];
…
Rule 63: **IF** [$H_2 \in 1$ **OR** $H_2 \in 2$] **AND** [$CH_4 \in 3$] **AND** [$C_2H_6 \in 3$] **AND** [$C_2H_4 \in 3$] **AND** [$C_2H_2 \in 3$] **THEN** [**D**$\in$ **3**];
Rule 64: **IF** [$H_2 \in 3$] **AND** [$CH_4 \in 3$] **AND** [$C_2H_6 \in 3$] **AND** [$C_2H_4 \in 3$] **AND** [$C_2H_2 \in 3$] **THEN** [**D**$\in$ **3**];

Stage of defuzzification. At this stage, the fuzzy information contained in the form of the authenticity of the linguistic term is transformed into a clearly defined meaning. The defuzzification is made according to the figure obtained by adding all the membership functions of the terms of the input variable. As a method of defuzzification, the right modal value method was adopted, which provides the greatest reliability in determining the degree of belonging of the output variables.

Testing of fuzzy neural network. The trained network was tested on an independent sample (values that were not used in training). For the convenience of analysis, the test data was broken according to known diagnoses into three groups. Test results for serviceable transformers whose concentration values do not exceed the values for level 1, from Table 1 are shown in Fig. 5.

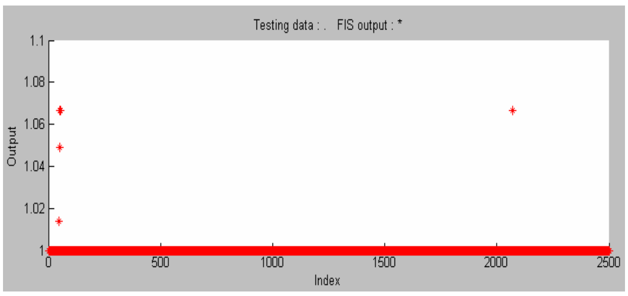
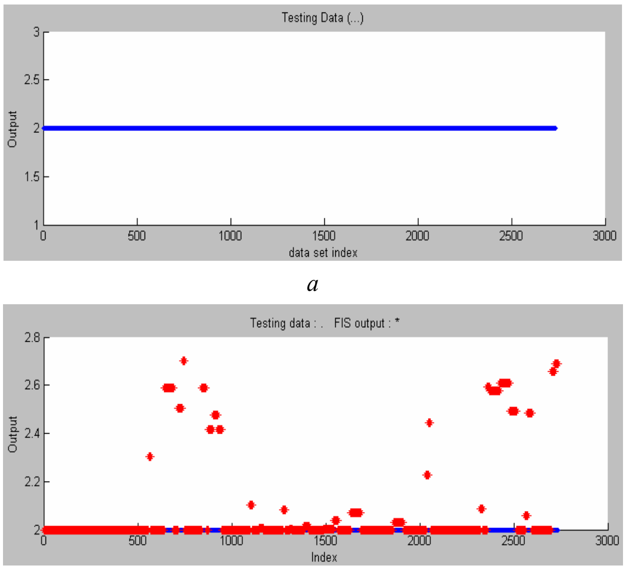


Fig. 5. Results of testing fuzzy neural network for CADG results of transformers not having defect

As can be seen from Fig. 5, the fuzzy neural network unambiguously classified the data presented to the recognition to level 1. Further, the trained neural network was presented to recognize the values of concentrations of dissolved gases that correspond to level 2. The test results are shown in Fig. 6.

Fig. 6 shows that the network accurately, but with varying degrees of belonging, carried all the results of the CADG to the level 2 submitted to the input. At the last stage of the testing for the input of the fuzzy neural network, the results of CADG were submitted, for equipment in which defects of various types were detected. It should be noted that in the sampling network fed to the input, the concentration of at least one of the gases corresponded to level 3.



a

b

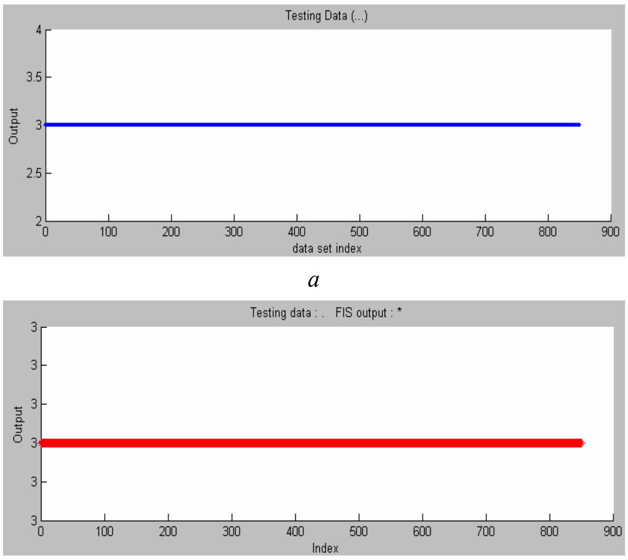
Fig. 6. Results of testing fuzzy neural network for the results of CADG transformers, whose gas concentrations correspond to level 2 (*a* – initial data, *b* – test results)

The test results are shown in Fig. 7.

As you can see from the Figure, the fuzzy neural network correctly recognized the defective condition of the transformers, too.

Analysis of the possibilities of a fuzzy neural network. Further, the results of CADG of serviceable transformers were submitted to the input of the fuzzy neural network, in which the gas concentrations corresponded to level 3. The reason for the increase in gas concentrations was the emergency operation of electrical networks (short-circuit, overvoltage, transformer overloading effects [13, 14]). And violations by operational personnel in the selection, transportation and storage of oil samples, as well as during testing. The results of the network are shown in Fig. 8.

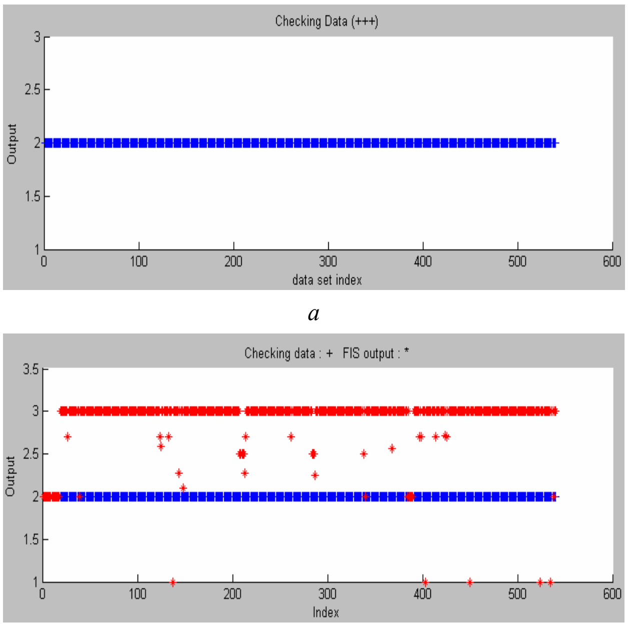
As can be seen from Fig. 8, out of 541 the results of CADG applied to the input to the defect-free state, the network classified only 5.



a

b

Fig. 7. Results of testing fuzzy neural network for the results of CADG defective transformers (*a* – initial data, *b* – test results)



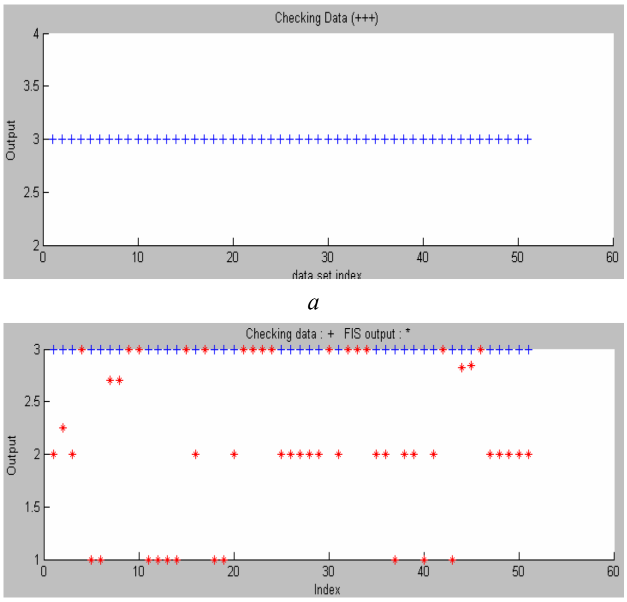
a

b

Fig. 8. Results of testing fuzzy neural network for the results of CADG defect-free transformers, in which gas concentrations corresponded to level 3 (*a* – initial data, *b* – test results)

The analysis performed showed that in these five oil samples the levels 3 corresponded to the values of only one of the five gases. The values of the concentrations of the remaining four did not exceed the detection limit by the chromatograph (conditionally equal to zero). Such gas content is not characteristic for a defective state, i.e. In the training sample, such data were not available, which probably allowed the network to make this diagnosis. Another 27 CADG results were attributed to the suspicious state by the network, i.e. level 2. In these oil samples, the concentration of only one of the five gases corresponded to level 3. The concentrations of the remaining four did not exceed the detection limit by the chromatograph or corresponded to level 1. All other results of the CADG presented to recognition were attributed to state 3 by the network, i.e. mistakenly recognized as defective, which is error of the first kind (false alarm).

No less interesting are the results of the operation of the fuzzy network, with the recognition of the state of the transformers based on the results of the CADG defective equipment, which are obtained in the early stages of defect development, when the gas concentrations do not exceed the upper limit of level 2. The results of the operation of the electric network are shown in Fig. 9. As can be seen from Fig. 9 out of 51 results submitted to the network input for only 15, the network was diagnosed a defective condition. For 25 samples of oils, with varying degrees of belonging, the network was diagnosed with a suspicious condition (level 2). It is noteworthy that the results of the CADG transformers of the Nelson River hydropower station, Northern Canada [16], which were received for 10 months and 5 days before their damage (1 and 2 results, respectively) were attributed to level 2 by the network. It should be noted that the expert system used by the company could not prevent damage to these transformers. However, according to the results of CADG, the fuzzy neural network has definitely not determined the defective state in these transformers, but only classified the results obtained as a result of the state of «suspicious concentrations». For 11 results of CADG, the fuzzy neural network diagnosed the absence of a defect, which is error of the second kind (missed target).



a

b

Fig. 9. Results of testing fuzzy neural network for the results of CADG defective transformers, in which the gas concentrations did not exceed the boundary values of level 2
(*a* – the initial data, *b* – the test results)

Analyzing the obtained results, it is necessary to recognize that the developed and trained neural network had to solve the mutually exclusive problem. On the one hand, in order to recognize the defects of equipment at an early stage of their development, the membership function for the defective state must be shifted to the lower range, on the other hand, to recognize the effect of emergency operation of the network, the membership function for the faulty state must be shifted to higher values. However, even in such a situation, a fuzzy neural network has successfully coped with the task, especially considering that an unmistakable recognition of emergency influences and defects at an early stage of development, based on the use of only the values of gas concentrations, is fundamentally impossible. At the same time, as shown in [6], the use as a criterion for the development of a defect, the nature of changes in gas concentrations in time, allows solving this problem with almost 100% certainty. Thus, the reliability of the diagnosis of a neural network is significantly influenced by both the diagnostic features used to make the diagnosis, and the decision rule.

In addition, the reliability of the diagnosis, which puts the neural network, is substantially limited by the peculiarities of the CADG method. This was clearly demonstrated by the example of recognition of a condition caused by an emergency response from the power grid or personnel errors. Since both the development of the defect, and the effect of abnormally high currents, voltages or temperatures, due to emergency operation of the network, lead to an increase in gas concentrations, then on the basis of an analysis of only the values of gas concentrations, it is not possible to determine the cause of gas evolution. Therefore, to expect an error-free diagnosis from the neural network would be extremely improper.

Conclusions:

1. A fuzzy neural network has been designed, trained and tested to interpret the results of CADG. In contrast to similar investigations, when training a neural network, the functions of belonging to linguistic terms were chosen taking into account the functions of the density distribution of gas concentrations for transformers with different states, which allowed to take into account both the peculiarities of the gas content of oils characteristic for non-hermetically sealed transformers and the operating conditions of this equipment.
2. Based on the results of the network check on an independent sample, it was found that the greatest difficulty in diagnosing by the boundary gas concentration criterion is the results of CADG obtained for serviceable transformers in which the concentrations of dissolved gases in the oil exceed their boundary values, as well as for defective transformers on early stage of defect development.
3. The performed analysis showed that the reliability of recognition of fuzzy neural networks has limitations that are determined by the features of the CADG method, the diagnostic features used and the chosen decision-making rule.

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