UDC 621.311: 621.311.6 https://doi.org/10.20998/2074-272X.2023.5.01

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Development of fuzzy classifier for technical condition ranking of power transformer

*The work **aim** is to develop a fuzzy classifier for technical condition ranking of power transformer under condition of vagueness and ambiguity diagnostic information. **Methodology**. The fuzzy classifier developing for technical condition ranking of power transformer was based on approach of using fuzzy set theory and optimization methods. The proposed approach for power transformer rank assessment by using a classifier was developed on the basis of Takagi-Sugeno fuzzy inference system. The input indicators choice is justified and their efficiency for classifier is evaluated by expert evaluation method. This makes it possible to formalize expert assessments regarding the development of power transformer defects. **Results**. The formalization of technical condition assessment of power transformer in knowledge base form, which implemented in expert system prototype for technical condition assessment, was carried out. The complex technical condition assessment for each functional unit of power transformer was determined based on expert evaluations with using the test and measurement parameters results. **Originality**. The considered approach to formalization of uncertainty regarding technical condition of power transformer allows building a deterministic decision-making scheme for further maintenance strategy, in which the ranking and decommissioning procedures for specific objects are implemented on the basis of objective criteria. **Practical value.** The proposed fuzzy classifier allows determination with a high probability degree of technical condition assessment of power transformer based on the test and measurement parameters results. Thus, an applied aspect of using the obtained scientific result is the possibility to objectively rank of power transformers park based on the identified possible defects and their development degree. This constitutes the prerequisites for determining the failure probability evaluation of power transformer at nearest observation period and emergency risk assessment in integrated electric power systems under power transformer failures.* References 36, tables 8, figures 12.

Key words: **fuzzy classifier, electrical equipment, technical condition assessment, defect, power transformer.**

Розглянуто питання обґрунтування і розробки інтелектуальної системи для підтримки прийняття рішень щодо визначення рангу технічного стану силового трансформатора. Запропоновано підхід для встановлення рангу силового трансформатора шляхом застосування класифікатора, розробленого на базі системи нечіткого виведення Такагі – Сугено. Побудовано ієрархічні структурні схеми визначення рівнів факторів технічного стану окремих функціональних вузлів та силового трансформатора в цілому. Розроблено нечіткий класифікатор для ранжування технічного стану силового трансформатора за результатами окремих випробувань і вимірювань. Виконана адаптація нечітких моделей оцінки технічного стану шляхом навчання нечіткого класифікатора на вибірках з протоколів обстеження парку силових трансформаторів різних типів і класу напруг. Виконано комплексну оцінку технічного стану та класифікацію рангу за сукупністю контрольованих параметрів силових трансформаторів енергокомпанії. Бібл. 36, табл. 8, рис. 12.

Ключові слова: **нечіткий класифікатор, електрообладнання, оцінка технічного стану, дефект, силовий трансформатор.**

Introduction. The current state of the electric power industry in the industrialized countries of the world is characterized by a significant degree of wear of power transformers (PTs) as the most common element of the electric power system. Accelerated renewal of the PT park requires colossal investments in the electric power industry and determines the need for a comprehensive approach to solving these problems, not limited to equipment replacement [1-3]. Table 1 presents statistical data on the distribution of characteristic damage of PTs 110-500 kV by functional nodes [4, 5].

Table 1

Statistical data on the distribution of PT damage by functional nodes according to the duration of operation

PT functional node	Number of damages according to the duration of operation of the ST					Total
	10 years	10-20 years	20-30 years	30-40 years	>40 years	
Magnetic core	0	0	1	0	0	1
Cooling system	2	14	13	1	0	30
Windings	23	25	23	28	12	111
On-load tap-changer	12	28	21	10	0	71
High-voltage bushings	15	37	38	31	9	130
Oil leak	12	16	19	11	3	61
Vandalism	3	6	10	1	1	21
Oil drain	12	22	22	14	5	75
Total	79	148	147	96	30	500

Figure 1 shows the statistics of the main reasons for PTs failures according to SIGRE data as of 2015 for the period from 1950 to 2009 [6].

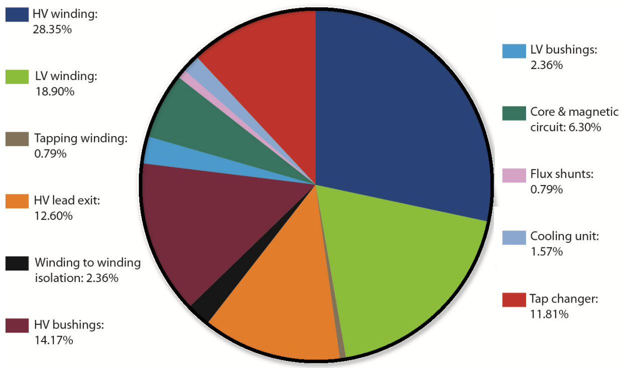

Fig. 1. The main causes of PT failures statistics for voltage more than 110 kV

In addition, most of the PT parks retain their operational capacity beyond the design life. It is urgent to improve the methods of diagnosing the technical condition of the equipment to determine the possibilities of its operation for 2-fold and more than the normative terms of operation [7-9].

Incorrect determination of the rank of the technical condition of the PT can lead to an erroneous calculation of the composition of the necessary volumes of diagnostic tests and measures for further operation [10].

Thus, the economic impracticality of prior equipment replacement is obvious, as well as the importance of timely detection of threatening defects, their further control with increasing reliability of determining the rank of the technical condition of the PT.

Analysis of literary sources and problem definition. Modern software and algorithms allow to significantly increase the reliability of solving such problems in conditions of uncertainty of diagnostic information. More reliable decisions regarding the ranking of the technical condition of PTs can be obtained when using intelligent decision support systems [11].

Currently, chromatographic analysis of dissolved gases (DGA) in PT oil is widely used to diagnose PT. Under the conditions of the occurrence and development of a defect inside the transformer, the composition and concentration of gases dissolved in the transformer oil intensively change both quantitatively and qualitatively [12].

Practically all available methods for evaluating the results of the DGA do not allow to clearly classify the technical condition of the PT based on the change in gas concentrations and, accordingly, cannot be used to assess the technical condition of the transformer at the observation time interval [13].

Table 2 presents certain results of some systems developed for diagnosing transformers based on DGA [14-16].

Table 2

Obtained results for some PT defect diagnosis systems

Number of PT	Diagnostic accuracy of the developed systems, %
711	90,3 – educational sample 93,81 – test sample
210	95,72 – educational sample 95,34 – test sample
711	96,2
33	90,91 – Dornenburg method 87,88 – modified Rogers method 90,91 – Rogers method 93,94 – IEC/IEEE method
820	90,49 – educational sample 93,54 – test sample

Quantitative indicators of diagnostic accuracy of the presented systems reflect the need to use methods that allow minimizing the error in assessing the technical condition of the PT.

The complexity of solving this problem is determined by the presence of a number of factors that simultaneously affect the concentration of gases in the oil: deterministic factors determined by the design of the PT, as well as stochastic factors that depend on the operating conditions of the PT.

A generalization of the results of basic and promising scientific works was carried out for the selection of software and algorithms for intelligent systems that allows obtaining reliable forecasting results in conditions of uncertainty [8-12].

Based on the results of the generalization, a technical and economic evaluation of production models (PM), semantic networks (SN), logical models (LM), artificial neural networks (ANN), fuzzy logic (FL), fuzzy neural networks (FNN), etc. was carried out [13-20].

Table 3 shows the characteristics of knowledge representation models for intelligent decision support systems.

It is obvious that among the listed models of the problem to be solved, models based on fuzzy neural networks are best suited [21]. They combine the advantages of such models of knowledge presentation as FL and ANN, which allows to compensate for the shortcomings inherent in each individual model.

Table 3

Technical and economic assessment of knowledge representation models

Name of the criterion	Knowledge representation model					
	LM	PM	SN	ANN	FL	FNN
1. Ability to operate with fuzzy data	-	+	-	+	+	+
2. Universality	-	-	-	+	-	+
3. Clarity of knowledge presentation	-	+	+	-	+	+
4. Modularity	+	+	-	+	-	+
5. Allowable time spent on building the model	+	+	-	+	+	+
6. Acceptable value	+	+	-	+	+	+
7. Ability to self-study	-	-	-	+	-	+
8. Efficiency coefficient	0,5	0,7	0,1	0,9	0,6	1

Based on the results of the analysis, it was decided to use FNN to build a fuzzy classifier based on the application of the Takagi-Sugeno fuzzy system model [22].

Therefore, **the goal of the article** is to improve the efficiency of the assessment of the technical condition of the power transformer by developing a fuzzy classifier to ensure the reliability of determining the rank of the technical condition of the power transformer.

To achieve the goal, the following tasks were solved:

- to develop a hierarchy of fuzzy assessment of the technical condition of the PT based on the aggregation of the most significant levels of factors affecting the technical condition;
- to develop an algorithm for conducting a fuzzy assessment of the technical condition of the PT based on a set of controlled parameters;
- to develop a fuzzy classifier for ranking the technical state of PT;
- to carry out a comprehensive fuzzy assessment of the technical condition of the PT in the conditions of information uncertainty in order to make effective preventive decisions regarding the strategy of further operation.

The concept of selecting parameters affecting the determination of the rank of the technical state of the PT. There are a number of diagnostic methods for determining the state of PT, but it is not easy to integrate their results into a single comprehensive assessment. The method based on fuzzy logic for calculating the health index proposed in [23] allows determining only the performance indicator of the insulation system. Over the past decades, various algorithms for diagnosing the state of PT have been proposed using intelligent information processing technology, such as the Bayes method [24], the method of evidentiary argumentation [25], the method of support vector machines [26], the method of artificial neural network [27]. When a PT defect occurs, it is often accompanied by a change in some parameters of the technical condition [28]. These algorithms have achieved good results in engineering practice, but there is a lack of analysis of the correlation of each parameter and the class of technical state of PT. In [29], when assessing the state of the transformer, each of the test indices and state rank corresponds to a separate pair of data sets. But the internal relationships between each test index were not considered in these works, so the types of PT damage cannot be diagnosed. On the other hand, the methods of assessing the condition of transformers based on the method of analysis of pairs of sets are the basis for the complex scoring method of assessing the technical condition by experts. This makes it possible to construct fuzzy matrices of expert evaluations using an analytical hierarchical process to determine weighting factors. However, the use of a complex scoring method for assessing the technical condition and analytical hierarchical process do not allow to completely avoid subjective disagreements of experts regarding the presence of a defect in the PT [30].

For the above reasons, this article makes an attempt to overcome the shortcomings of the considered approaches and methods of determining the comprehensive assessment of the technical condition of the PT.

The development of a fuzzy classifier involves the implementation of several main stages. At the initial stage of creating a classifier, it is necessary to select the factors that are most significant in determining the rank. Selection of the main parameters is also important, since the assessment of the technical condition rank of PT is characterized by a large number of factors that have certain differences for different classes of technical condition. The solution to this problem is possible using the method of expert evaluations for ranking the compared objects.

The proposed method of expert evaluations is based on the use of a fuzzy comprehensive evaluation of the object, the functioning of which is influenced by numerous factors.

The practice of conducting diagnostic tests on PT shows that when making a diagnostic hypothesis regarding the presence of a defect, there should be several factors that are considered and determined in the evaluation process. Since it is usually very difficult to make a decision using a classical mathematical method, fuzzy complex estimation is able to solve the multi-factor assessment decision-making problem. This assessment method is based on existing evaluation standards and fuzzy conversion of actually measured data or data with significant uncertainty, incomplete information. Compared to other methods, it is a comprehensive, objective and integrated method of evaluating results.

The algorithm for conducting a fuzzy assessment of the technical condition of the PT is as follows.

1. Determination of the set of X levels of factors influencing the technical condition of the PT, which requires assessment:

$$X = \{x_1, x_2, \dots, x_n\}; \tag{1}$$

where x_i is the i-th factor that can affect the technical condition of the PT and has a certain degree of ambiguity; n is the total number of factors that can affect the technical condition of the PT.

2. Formation of the set V of expert evaluations:

$$V = \{v_1, v_2, \dots, v_n\}; \tag{2}$$

where v_i is the i-th comprehensive result of the expert's comprehensive assessment; n is the total number of expert assessments regarding the technical condition of the PT.

3. Formation of the complex matrix of fuzzy relations of expert evaluations R:

$$R = \begin{vmatrix} r_{11} & \cdots & r_{1j} \\ \vdots & \ddots & \vdots \\ r_{j1} & \cdots & r_{ij} \end{vmatrix}, \tag{3}$$

where $r_{ij} \in [0, 1]$ is the element of the matrix of fuzzy relations between damage to functional nodes and the consequences of these damages.

4) Definition of the system of weighting coefficients W:

$$W = (w_1, w_2, \dots, w_n), \quad \sum_{i=1}^{n} w_i = 1, \tag{4}$$

where w_i is the i-th weighting coefficient reflecting the significance of each assessment factor x_i; n is the total number of weighting coefficients for assessing the significance of factors with regard to the impact on the assessment of the technical condition of the PT.

5) Definition of the set B of the fuzzy comprehensive assessment of the technical state of the PT. The equation of the fuzzy comprehensive assessment of experts regarding the technical condition of the PT

$$B = \max\{b_1, b_2, \dots, b_n\}, \tag{5}$$

where $b_j = \sum_{i=1}^{m} w_j \cdot r_{ij}$, j = 1, 2, ..., n is the j-th fuzzy comprehensive assessment of the technical condition of the PT; n is the total number of fuzzy comprehensive assessments of the technical condition of the PT.

An expert group consisting of n highly qualified specialists in the operation and repair of PTs is formed to carry out the work on the fuzzy comprehensive evaluation of technical state using the method of expert evaluations. The formation of the group began with the selection of candidates and their further evaluation using the Delphi method [31].

To determine the technical condition of the olive PT, based on the results of individual tests and measurements, a linguistic mathematical model was developed, which includes the rules of fuzzy logical inference, the term-set and the function of the input parameters belonging to one or another linguistic quantity. Figure 2 presents a fragment of a hierarchical structural diagram of a fuzzy logical inference about the technical condition of an oil transformer on the basis of defined separate levels of technical condition factors [32].

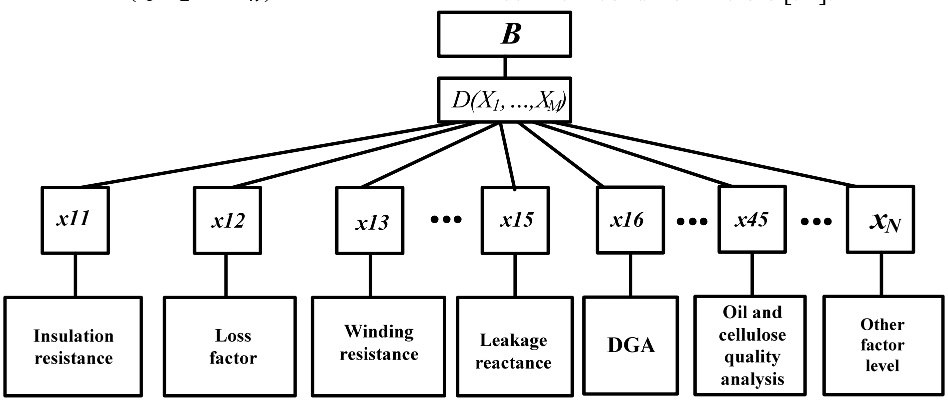

Fig. 2. The hierarchical structural scheme of fuzzy logical conclusion for PT technical condition

The model contains the rules of Takagi-Sugeno fuzzy logical inference, terms and functions of belonging of the input parameters to one or another linguistic quantity. The knowledge base of the prototype of the expert system for diagnosing the technical condition of the PT is based on a hierarchical representation and consists of a system of built-in knowledge bases. An integral assessment of the technical condition is carried out by aggregating inferences regarding the type of the PT defect based on individual test results, using relevant knowledge bases.

Fuzzy logic analysis includes three sequential processes, namely: fuzzification, fuzzy inference, and defuzzification. Fuzzification transforms, for example, a clear gas ratio into a fuzzy input set. The selected fuzzy logic inference system is responsible for obtaining inferencees from fuzzy rules based on the knowledge of «if-then» linguistic statements. Each rule consists of two components, in which there is the preceding part («if») and the following part («then»). With the help of a fuzzy approach, partial belonging to a certain class of technical condition (determined by the value of the belonging function) can increase the number of relevant inferences compared to the traditional criteria for assessing the technical condition of the PT, which are regulated by regulatory and technical documentation [6, 32].

For example, the linguistic rule for determining the assessment of technical condition indicators based on the results of the DGA has the following form: if «C2H2/C2H4 is 0, CH4/H2 is 2, and C2H4/C2H6 is also 0, then the type of defect that corresponds to this combination of ratios is D7», that is, a low-temperature defect (overheating) T<300 °C.

The defuzzification function then transforms the original values back into crisp values.

All inputs of the fuzzy logical inference system have membership functions, the basic forms and parameters of which are presented in detail in [32]. To take into account the objectively existing tolerance of the recognized defect to the change of parameters in a certain range, the trapezoidal membership functions are used.

At the initial stage, each expert was offered 7 indicators according to their significance for ranking the technical state of the PT:

- x1 – the level of the technical condition factor of the PT windings (Fig. 3);
- x2 – the level of the factor of the technical condition of the magnetic core of the PT (Fig. 4);
- x3 – the level of the factor of the technical condition of high-voltage bushings of the PT (Fig. 5);
- x4 – the level of the factor of the insulation characteristics of the transformer oil of the PT (Fig. 6);
- x5 – the level of the factor of the on-load tap-changer switch (Fig. 7);
- x6 – the level of the factor of the technical condition of other PT nodes (Fig. 8);
- x7 – the level of the factor of other PT operation indicators (Fig. 9).

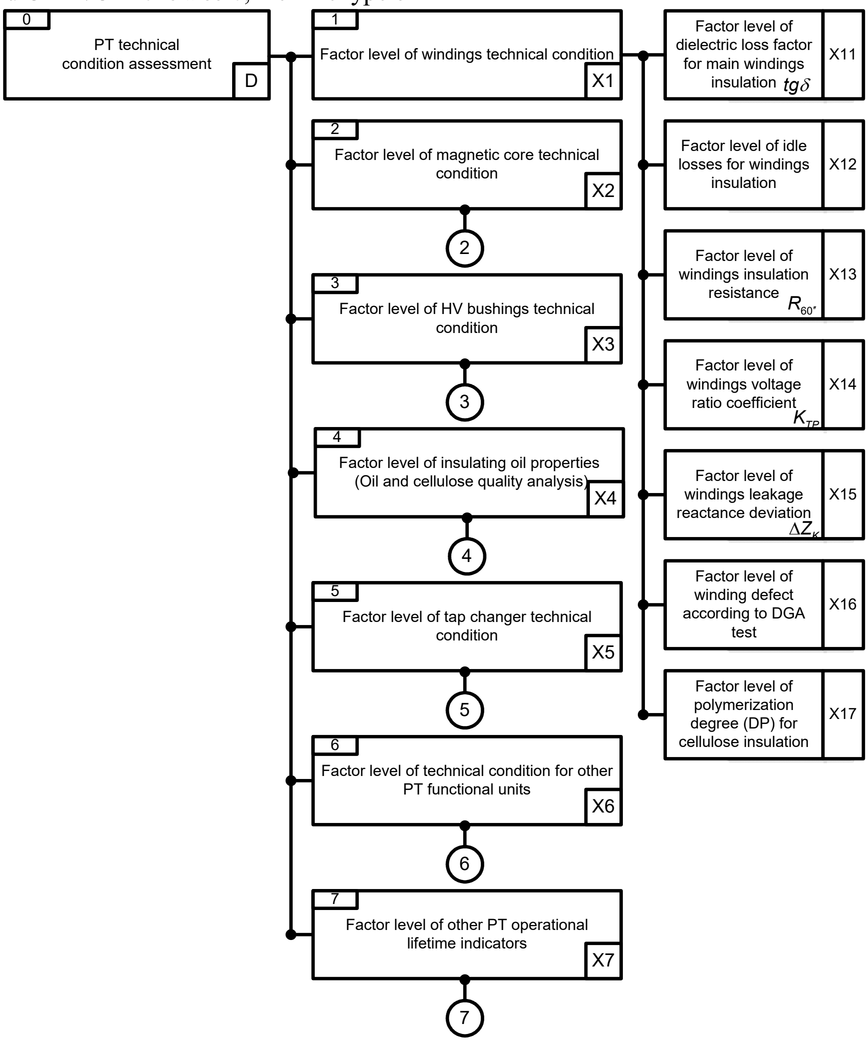

Fig. 3. The hierarchical structural scheme of PT technical condition assessment

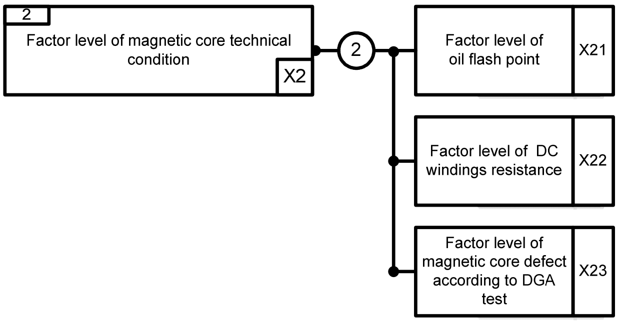

Fig. 4. The hierarchical structural scheme of factor level assessment for PT magnetic core

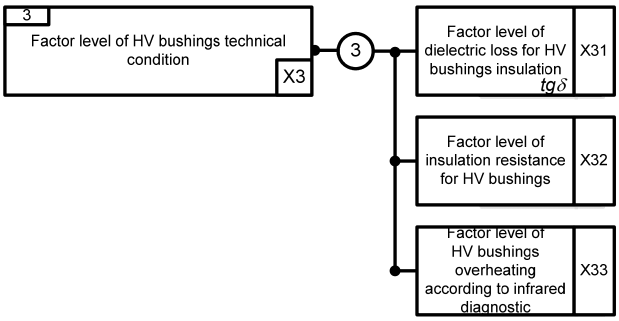

Fig. 5. The hierarchical structural scheme of factor level assessment for PT HV bushings

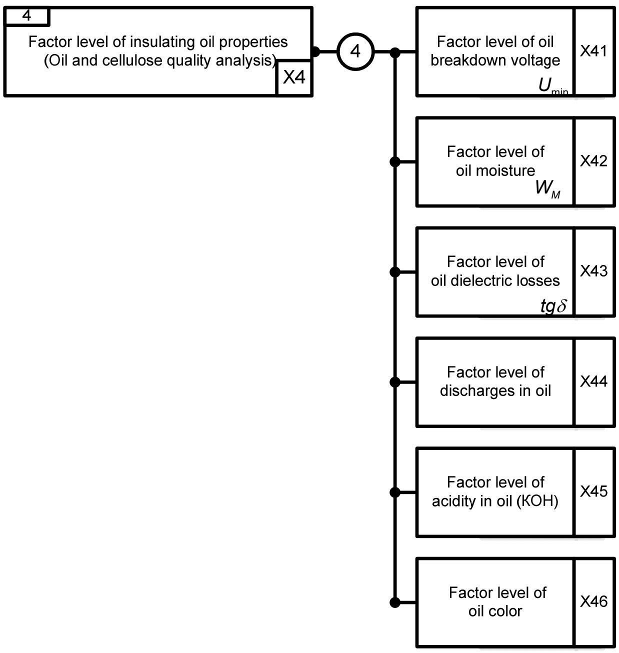

Fig. 6. The hierarchical structural scheme of factor level assessment for insulating oil properties (oil and cellulose quality analysis)

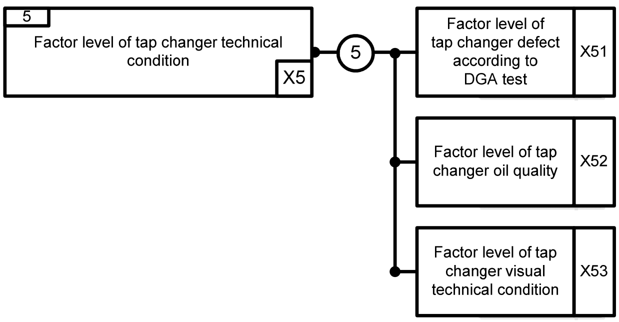

Fig. 7. The hierarchical structural scheme of factor level assessment for tap changer technical condition

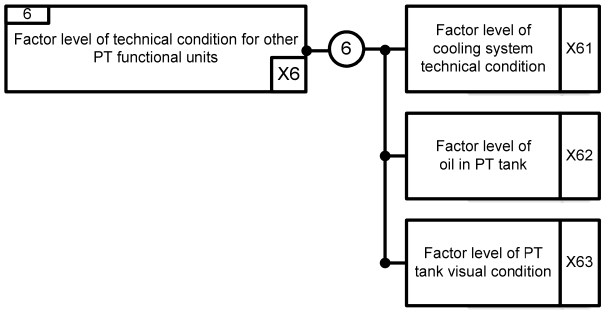

Fig. 8. The hierarchical structural scheme of factor level assessment for technical condition for other PT functional units

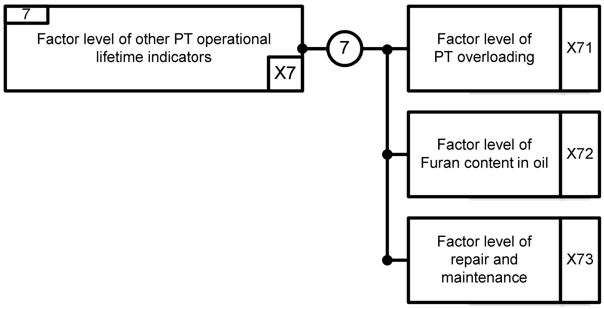

Fig. 9. The hierarchical structural scheme of factor level assessment for other PT operational lifetime indicators

Assessment of the technical condition of the PT by experts depends on overcoming the uncertainty of information:

- it is impossible to determine the state by one measurement, based on one method;
- reliable diagnosis is based on: several types of diagnosis; dynamics of changes in characteristics;
- impossibility of applying the same diagnosis criteria for different constructions and voltage classes;
- the reliability of the diagnosis results should be achieved with minimum costs for obtaining them.

Construction of a fuzzy classifier for ranking the technical condition of the PT. After determining the levels of factors of the technical state of the PT, the operating conditions of the PT are classified in order to establish the assessment of each factor for a comprehensive fuzzy assessment [33]. The operating conditions of the PT are classified as good, acceptable, requiring caution and risky in this article expressed as a set of expert assessments $V = \{v_1, v_2, v_3, v_4\}$ = {good, acceptable, requiring caution, risky}.

The operating condition «good» means that the test sample of transformer operation data is normal, and each technical condition parameter deviates slightly from the monitored values. The probability of a defect occurring is low and long-term operation within the limits of permissible deviations of the monitored parameters is available.

«Acceptable» operating conditions mean that the PT has been operated for a certain period of time, and satisfactory test data or reliability of a certain individual monitored parameter of the technical condition is slightly less than the limit of acceptable deviations. Since the data is reliable, the operation of the PT can be continued, and the probability of failure is low.

The operating condition «Requires caution» means that the test data deviates from the normal state during the test period. Some parameters of the technical condition indicate that a defect may exist, thus the probability of damage is increased, and although the transformer may continue to operate, the operating interval must be shortened.

The operating condition «risky» means that the overall operational properties of the PT are below average. Most of the obtained monitored parameters exceed the values regulated by the Standards, and the probability of failure is high.

Table 4 presents the semantic definition of the ratio of the rank of the technical condition and operating conditions of the PT.

Table 4
Semantic definition of the range of changes in the rank of the technical state of the PT

Range of change of value B	Semantic definition of assessment of the technical condition of the PT
0…0,25	Good technical condition of the PT. Continuation of operation without restrictions. Very low failure rate (VL)
0,25…0,5	A low degree of deterioration of the technical condition of the PT. Continuation of operation without restrictions. Low failure rate (L)
0,5…0,75	The average degree of deterioration of the technical condition of the PT. A slight degree of development of the defect. More frequent monitoring of parameters of technical state of the PT. Medium failure rate (M)
0,75…1,0	The technical condition shifted from a state of deterioration to a state of failure. A significant degree of defect development. High failure rate (H)

Linguistic variable B «fuzzy comprehensive assessment of the technical state of the PT», presented in Table 4 is represented by the basic term-set $T = \{T_{VL}, T_L, T_M, T_H\}$, where T_{VL}, T_L, T_M, T_H are the terms corresponding to very low, low, medium and high levels of deterioration of the technical condition of the PT. Graphs of membership functions of the term-set of the linguistic variable B are shown in Fig. 10.

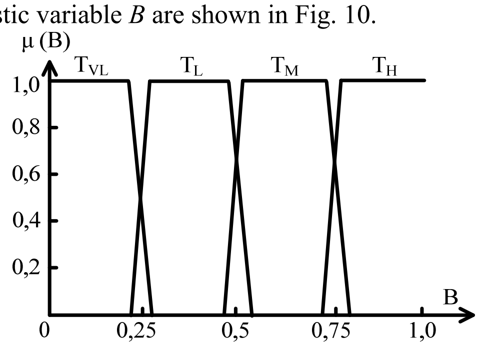

Fig. 10. The membership functions of linguistic variable B

Thus, the results of each type of diagnosis are classified independently, and then the final inference is made taking into account all expert assessments.

To determine the rank of the technical state of the olive PT, a linguistic model of the classifier based on the use of the fuzzy logic apparatus was developed [32, 34, 35].

The fuzzy model of the classifier of the comprehensive assessment of the PT state is built on the basis of the adaptive neuro-fuzzy network ANFIS (Adaptive Network-based Fuzzy Inference System), which is a hybrid multilayer artificial neural network of a special structure without feedback and allows implementing system models in the form of fuzzy production rules.

The fuzzy classifier for ranking the technical condition of the PT is presented in the form

$$B = F(X, V, C, W), \tag{6}$$

where $X = \{x_1, x_2, \ldots, x_n\}$ is the input vector of rank estimates of indicators of factor levels of the fuzzy model of the classifier; $V = \{v_1, v_2, \ldots, v_q\}$ is the vector of parameters of the membership functions of a comprehensive assessment by an expert of indicators of the levels of factors of the fuzzy model of the classifier; $C = \{c_1, c_2, \ldots, c_q\}$ is the vector of parameters of fuzzy terms from the knowledge base of the fuzzy classifier model; $W = \{w_1, w_2, \ldots, w_n\}$ is the vector of weight coefficients of fuzzy rules of the fuzzy classifier model; n is the total number of fuzzy rules in the knowledge base of the fuzzy classifier model; q is the total number of terms of the fuzzy model of the classifier; F is the «input-output» communication operator of the fuzzy classifier model.

The values of inputs, outputs and synaptic weights of the hybrid neural network are in the range [0, 1].

Figure 11 shows an example of a neural network representation of the rules of a fuzzy classifier for 2 levels of influencing factors on the technical condition of the PT.

The ANFIS network uses a hybrid learning algorithm. Neurons in the ANFIS network have a different structure and purpose, which correspond to the fuzzy inference system and implement the main subsequent stages of its operation.

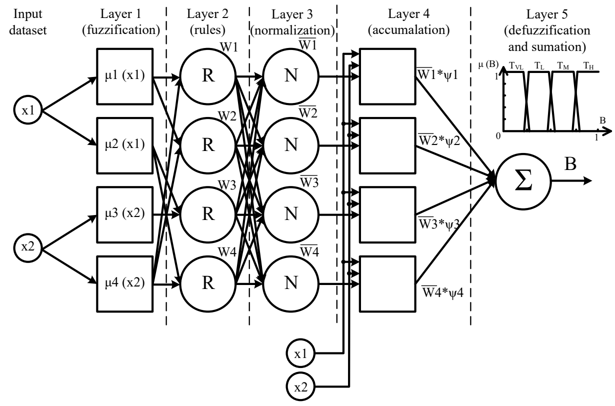

Fig. 11. The neural network representation of fuzzy classifier rules for two factors levels affecting PT technical condition

Layer 1. Fuzzification using membership functions of input variables. The first adaptive layer of the ANFIS network contains neurons that calculate the values of the membership functions of the input variables $\mu_i(x_1)$ and $\mu_j(x_2)$, where x_1 and x_2 are the input variables, i=1, 2 and j=3, 4. The adaptability of the layer is achieved by selecting the type of membership functions of the input variables.

Layer 2. Aggregation (determining the degree of truth of conditions) by processing the basis of fuzzy linguistic rules. The second fixed layer of the ANFIS network contains neurons that calculate the products of the values of the membership functions obtained on the first layer:

$$W_i = \mu_i(x_1) \cdot \mu_j(x_2), \tag{7}$$

where W_i are the synaptic weights of the network.

Layer 3. Activation (determining the degrees of truth of statements) by normalizing the activation levels of fuzzy rules. The third fixed layer of the ANFIS network contains neurons that calculate the normalized activation levels of the fuzzy rules:

$$\overline{W}_i = W_i / \left(W_1 + W_2 + W_3 + W_4\right). \tag{8}$$

Layer 4. Accumulation (combination of degrees of truth) using membership functions of the output variables. The fourth adaptive layer of the ANFIS network contains neurons that calculate the values of the membership functions of the output variables, as well as the product of the values of the synaptic weights and the membership functions:

$$\overline{W}_i \cdot \psi_i = \overline{W}_i \cdot \psi_i(x_1, x_2, c_i), \quad (9)$$

where ψ_i are the values of the membership functions of the output variables; c_i are the parameters of fuzzy terms of membership functions from the knowledge base.

Layer 5. Defuzzification (transition to clarity) with obtaining a clear value of the original variable. The fifth fixed layer of the ANFIS network contains a neuron that calculates the sum of the product of the values of the membership functions of the output variables and synaptic weights

$$\sum_{i=1}^{M} \overline{W}_i \cdot \psi_i . \quad (10)$$

Layer 6 consists of elements that determine the maximum value of belonging among all the rules that specify the rank label of the technical condition of the PT.

Layer 7 consists of one element containing the rank index of the technical condition of the PT with the maximum value of belonging.

Figure 12 presents the general structure of the neural network built for the fuzzy classifier for assessing the technical condition of the PT. Neurons corresponding to the rules, which set labels of a specific rank, are placed in separate groups.

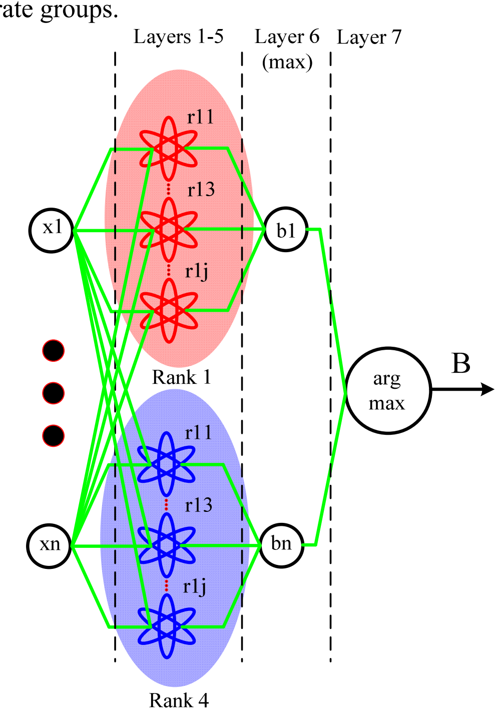

Fig.12. The fuzzy classifier architecture for identification of PT technical condition rank

Criterion values of the parameters used in the fuzzy model are statistically averaged over a large set of operating PTs. The actual modes of operation of each specific PT may differ. This requires adapting fuzzy models to real operating conditions by adjusting parameters.

In full, the input arguments are unknown, that is, there is uncertainty in the assessment of the technical condition of the PT. In this case, it is recommended to use machine learning algorithms in which there are no obvious logical relationships between parameters, but it is necessary to have a training sample. The study was conducted using statistical information on PT failures and the results of diagnostic procedures from functioning PTs that were registered in the energy system of Ukraine.

Tuning a fuzzy model consists in finding such parameters that minimize the deviation between the desired and actual behavior of the model. The algorithm for setting up the adaptive neuro-fuzzy network ANFIS consists of two stages [32, 35].

Stage 1 (direct flow of the algorithm). We set the initial values of the parameters of the first adaptive layer, make calculations on the second and third layers, determine the parameters of the fourth adaptive layer and calculate the value of the identification error function. If the value of the identification error function is within the acceptable limits, then the training of the adaptive neuro-fuzzy ANFIS network is finished, otherwise we proceed to the second stage.

Stage 2 (reversal of the algorithm). Using the method of backpropagation of the identification error, we refine the parameters of the first adaptive layer.

It is assumed that the parameters of the membership functions should be selected in such a way as to preserve the linear ordering of the terms.

It is planned to improve the developed system by adjusting the weighting coefficients for assessing the significance of factors regarding the impact on the assessment of the technical condition of the PT. The adjusting here means the solution of the problem of optimizing the weighting coefficients for assessing the significance of factors with regard to the impact on the assessment of the technical condition of the PT.

The task of adjusting a fuzzy classifier model is performed in [32]:

$$RMSE = \sqrt{\frac{1}{M} \cdot \sum_{r=\overline{1,M}} \left[B^r - F\left(X^r, V, C, W\right)\right]^2} \to \min .$$

where X^r is the input vector in the r-th row of the fuzzy sample; B^r is the output vector in the r-th row of the fuzzy sample in the form of a fuzzy number; r is the row number in the fuzzy sample used in the process of optimizing the parameters of the fuzzy classifier model, and $r = \overline{1, M}$; where M is the number of data pairs representing the fuzzy sample.

For this, the fmincon function of the Optimization Toolbox package of the MATLAB system is used [32]. That is, a sample is taken from the protocols of diagnostic measurements and tests of the investigated PT of electricity supplier companies with a clear conclusion.

After training a fuzzy classifier model, its performance is analyzed using a test sample. Comparison of the results of the fuzzy classifier model with the actual defect justifies the high efficiency and accuracy of identification of the proposed model.

The training of the fuzzy classifier was carried out on a test sample of 250 PTs examination protocols, which included 100 protocols with no defects and 150 protocols with signs of defects of various types. The results of testing the reliability of the fuzzy classifier on training samples showed that the classifier correctly identified 241 out of 250 technical states of the PTs. The error of classification of the technical state of the PTs RMSE was 1.6 %, which is an acceptable result.

Table 5 presents a fragment of the results of determining the assessment of the technical condition of the PTs according to the results of the DGA on the control sample. The developed fuzzy classifier system showed a fairly high accuracy during testing. The classification error did not exceed 5 %.

Table 5

The results of the assessment of the technical condition of the oil PT according to the results of the DGA on a control sample by a group of experts

No.	Transformer type	Identification of the state of the PT according to the results of the measurement of DGA	
		SOU-N EE 46.501-2006	A classifier based on the theory of fuzzy sets
1	TDCG-400000/330	Thermal defect T > 700 °C	Thermal defect T > 700 °C. $\mu^H(B)$=1,00
2	TDCG-10000/110	Not specified	Low power discharges. $\mu^M(B)$=0,6
3	TDTG-10000/110	Not specified	High power discharge. $\mu^H(B)$=1,00
4	TDC-400000/330	Not specified	Thermal defect T > 700 °C. $\mu^H(B)$=1,00
5	TRDCN-63000/110	Thermal defect T = 300-700 °C	Thermal defect T =150-300 °C. $\mu^L(B)$=0,24; Thermal defect T = 300-700 °C. $\mu^H(B)$=0,76
6	ATDCTG-240000/220	Thermal defect T > 700 °C	Thermal defect T > 700 °C. $\mu^H(B)$=1,00
7	TDTN-63000/110	Not specified	High power discharge. $\mu^H(B)$=1,00
8	ATDCTN-250000/500	Thermal defect T > 700 °C	Thermal defect T > 700 °C. $\mu^H(B)$=1,00
9	TDCG-315000/110	High power discharge	Low power discharges. $\mu^L(B)$=0,30; High power discharge. $\mu^M(B)$=0,7
10	TDTN-40000/110	Thermal defect T > 700 °C	Thermal defect T > 700 °C. $\mu^H(B)$=1,00
11	ODTGA-80000/220	High power discharge	High power discharge. $\mu^H(B)$=1,00

Modelling of a comprehensive fuzzy assessment of the technical condition of the PT under conditions of information uncertainty. During the next test and measurement of the parameters of the technical condition of the PT TDC-400000/330 according to the results of the DGA, the concentrations of gases dissolved in the transformer oil were registered. Exceeding the limit values of concentrations and relative growth rates of dissolved gases by more than 10 % per month recorded in several recent measurements indicates the presence of a progressive defect in the transformer.

To carry out work using the method of expert evaluations based on a fuzzy comprehensive evaluation, an expert group of 5 highly qualified specialists in the operation and repair of PTs was created, each of whom was assigned his/her own number (E1,...,E5). The formation of the group began with the selection of candidates and their further evaluation. Based on a subjective assessment, the expert chose a set of parameters of each functional node of the PT.

At the initial stage, each expert was offered 33 indicators according to their importance to determine the assessment of the technical condition of the PT. The method presented in [34, 35] was used to evaluate experts.

At the next stage, the experts assessed the technical condition of functional nodes and operating conditions with the corresponding determination of the weighting coefficients of indicators of the technical condition of the PT.

According to the developed algorithm for conducting a fuzzy assessment of the technical condition of the PT, the results of determining the set B of the fuzzy comprehensive assessment of the technical condition of the PT are summarized in Table 6-8.

Table 6

The results of determining the technical condition indicators of the oil PT based on the results of a comprehensive examination by a group of competent experts

Expert code	Rank assessments of indicators of the technical condition of the PT X										
	X1	X11	X111	X12	X121	X13	X131	X16	X17	X2	X3
E1	1	2	3	1	2	1	1	1	1	1	2
E2	1	1	2	1	3	1	1	1	2	1	2
E3	1	2	2	1	2	1	1	2	1	1	1
E4	1	3	5	1	3	1	1	1	2	1	2
E5	1	1	3	1	2	1	1	2	1	1	1
Expert code	Rank assessments of indicators of the technical condition of the PT CT X										
	X4	X41	X42	X43	X5	X6	X61	X7	X71	X73	X731
E1	1	1	3	2	3	3	1	1/3	1	2	1
E2	1	1	3	3	1	5	1	1/4	1	2	1
E3	1	1	3	3	2	4	2	1/3	1	2	1
E4	1	1	3	2	3	5	1	1/3	1	2	1
E5	2	1	3	3	2	4	1	1/4	1	1	1
Expert code	Rank assessments of indicators of the technical condition of the PT CT X										
	X7311	X7312	X7313	X7314	X732	X7321	X7322	X7323	X7324	X733	X734
E1	1	1	5	1/2	3	4	1/4	3	2	1	2
E2	1	2	4	1	3	1	1/4	2	2	1	1
E3	1	1	4	1/3	3	3	1/4	2	1	1	2
E4	1	1	5	1	3	3	1/5	3	2	1	1
E5	1	2	3	1/2	2	5	1/3	3	3	1	1

Table 7

The results of determining the weighting coefficients of indicators of the technical condition of the oil PT based on the results of a comprehensive examination by a group of competent experts

Weight coefficients of indicators of factor levels of the technical condition of the PT W										
X1	X11	X111	X12	X121	X13	X131	X16	X17	X2	X3
0,2658	0,6167	0,3790	0,3833	0,3105	0,1337	0,5	0,35	0,1768	0,5	0,3233
X4	X41	X42	X43	X5	X6	X61	X7	X71	X73	X731
0,3039	0,1524	0,4571	0,3905	0,43	0,4285	0,2467	0,0803	0,1171	0,1822	0,1036
X7311	X7312	X7313	X7314	X732	X7321	X7322	X7323	X7324	X733	X734
0,1390	0,1948	0,5770	0,0892	0,2858	0,3391	0,0295	0,2916	0,2227	0,4333	0,5667

Table 8

The results of determining the rank of the technical condition of the oil PT based on the results of a comprehensive examination by a group of competent experts

Indicator name	Indicator designation	Term-sets of a linguistic variable *B*			
		Very low	Low	Medium	High
		$\mu^{VL}(B)$	$\mu^{L}(B)$	$\mu^{M}(B)$	$\mu^{H}(B)$
Electrical tests	B_{X1}	0,082422	0,405655	0,511922	0
Insulating properties	X11	0,133658	0,39363	0,472712	0
tg δ of insulation	X111	0	0,258	0,742	0
Electrical strength	X12	0	0,425	0,575	0
Leakage current	X121	0	0,725	0,275	0
Insulation resistance level	X13	1	0	0	0
Direct current resistance	X131	0	0,025	0,975	0
DGA	X16	0,195	0,495	0,31	0
Degree of polymerization of paper insulation DP	X17	0	0,4	0,6	0
Condition of the magnetic core	B_{X2}	0	0,825	0,175	0
High-voltage bushings	B_{X3}	0,1	0,65	0,25	0
Condition of transformer oil	B_{X4}	0,030476	0,487505	0,482019	0
Oil breakdown voltage	X41	0,2	0,8	0	0
Oil moisture	X42	0	0,4	0,6	0
tg δ of oil	X43	0	0,468	0,532	0
On-load tap-changer	B_{X5}	0,2	0,8	0	0
Other nodes	B_{X6}	0,167667	0,726833	0,1055	0
Cooling system	B_{X61}	0,2	0,7	0,1	0
Other factors	B_{X7}	0,151045	0,651077	0,197878	0
Overload	B_{X71}	0,2	0,6	0,2	0
Repairs and technical inspection of the PT	B_{X73}	0,086667	0,556667	0,356667	0
Environmental factors	B_{X731}	0,249115	0,600815	0,15007	0
Ambient temperature	X7311	0,15	0,6	0,25	0
Air humidity	X7312	0,1	0,65	0,25	0
Aggressive gases	X7313	0,3	0,6	0,1	0
Wind speed	X7314	0,4	0,5	0,1	0
History of operation	B_{X732}	0,131613	0,61589	0,252497	0
Oil temperature	X7321	0,15	0,7	0,15	0
Extraneous noises	X7322	0,2	0,6	0,2	0
Number of short circuits	X7323	0,1	0,5	0,4	0
The number of relay protection trips	X7324	0,1	0,65	0,25	0
The records of the PTs similar in power and construction	X733	0,2	0,5	0,3	0
Inspection and repair protocols	X734	0	0,6	0,4	0
General evaluation of the technical condition of the PT	Qualitative assessment of B	0,1115	0,4815	0,4069	0
	Quantitative assessment of B	0,279			

According to the results of the calculations for determining the assessment of the technical condition of the PT, the rank is characterized as «Low degree of deterioration of the technical condition of the PT. Continuation of exploitation without restrictions» with a degree of 0.279.

Based on the results of the inspection, a technical report was sent to the power company, which includes an expert opinion on the technical condition of the PT, recommendations on the scope of necessary diagnostic, preventive, and repair measures, protocols based on the control results, as well as maps and diagrams that clearly illustrate the current technical condition.

Conclusions.

1. The task of assessing and ranking the technical condition of power transformers by using a classifier developed on the basis of fuzzy set theory is formulated. Hierarchical structural schemes for determining the levels of factors of the technical condition of individual functional nodes and the power transformer as a whole have been developed.

2. An algorithm and a fuzzy classifier of the results of the assessment of the technical condition of the power transformer have been developed, which are based on multi-parameter aggregation of the states of individual

functional units, which allows to increase the efficiency of the assessment of the technical condition of the power transformer. This, in turn, makes it possible to plan financial costs for the performance of a certain amount of repair work and minimize the risk of failures at the stage of the life cycle of power transformer operation in conditions of uncertainty of diagnostic information.

3. In order to increase the efficiency of recognizing classes of the technical condition of power transformers, the fuzzy classifier developed on the basis of the ANFIS adaptive neural network and the Takagi-Sugeno fuzzy inference system was adapted to real operating conditions by adjusting the model parameters using statistical information about the failures of power transformers and the results of diagnostic procedures of functioning power transformers, which were registered in the energy system of Ukraine. The relative error of identifying the technical state RMSE is 1.6 %, which is no more than 5 % and can serve as an acceptable result of increasing the reliability of determining the rank of the technical state. Avoiding the subjective disagreements of experts regarding the presence of a defect in a power transformer is achieved by harmonizing expert assessments using the Delphi method.

4. A comprehensive fuzzy assessment of the technical condition of the power company's actually functioning power transformers in conditions of information uncertainty was carried out, and a list of recommendations regarding the strategy for their further operation was formed [36].

Conflict of interest. The authors of the article declare that there is no conflict of interest.

REFERENCES

1. Silva J., Sumaili J., Bessa R.J., Seca L., Matos M., Miranda V. The challenges of estimating the impact of distributed energy resources flexibility on the TSO/DSO boundary node operating points. *Computers & Operations Research*, 2018, vol. 96, pp. 294-304. doi: https://doi.org/10.1016/j.cor.2017.06.004.

2. Shiwen Y., Hui H., Chengzhi W., Hao G., Hao F. Review on Risk Assessment of Power System. *Procedia Computer Science*, 2017, vol. 109, pp. 1200-1205. doi: https://doi.org/10.1016/j.procs.2017.05.399.

3. Haes Alhelou H., Hamedani-Golshan M., Njenda T., Siano P. A Survey on Power System Blackout and Cascading Events: Research Motivations and Challenges. *Energies*, 2019, vol. 12, no. 4, art. no. 682. doi: https://doi.org/10.3390/en12040682.

4. Bubenchikov A.A., Nurakhmet Y.Y., Molodikh V.O., Rudenok A.I. Are most characteristic faults in the power equipment. *International Research Journal*, 2016, vol. 5, pp. 56-58. doi: https://doi.org/10.18454/IRJ.2016.47.290.

5. Alekseev BA *Condition monitoring (diagnostics) of large power transformers*. Moscow, Publishing House of the NTs ENAS, 2002. 261 p. (Rus).

6. *CIGRE WGA2.37, Transformer Reliability Survey*, CIGRE Technical Brochure 642, December 2015.

7. Pirotti O.Y., Balenko O.I., Brechko V.O., Huzin M.Y., Gontar J.G. Analysis of construction principles and functionality of high-voltage power transformer condition monitoring systems. *Bulletin of the National Technical University "KhPI". Series: Energy: Reliability and Energy Efficiency*, 2020, no. 1, pp. 61-70. (Ukr). doi: https://doi.org/10.20998/2224-0349.2020.01.09.

8. Shutenko O. V., Baklay, D. N. Analysis of the functionality of expert systems used to diagnose the condition. *Bulletin of the National Technical University "KhPI". Series: Energy: Reliability and Energy Efficiency*, 2011, no. 3, pp. 179-193. (Rus).

9. Shutenko O. Method for Detection of Developing Defects in High-Voltage Power Transformers by Results of the Analysis of Dissolved Oil Gases. *Acta Electrotechnica et Informatica*, 2018, vol. 18, no. 1, pp. 11-18. doi: https://doi.org/10.15546/aeei-2018-0002.

10. Shutenko O., Kulyk O. Comparative Analysis of the Defect Type Recognition Reliability in High-Voltage Power Transformers Using Different Methods of DGA Results Interpretation. *2020 IEEE Problems of Automated Electrodrive. Theory and Practice (PAEP)*, 2020, pp. 1-6. doi: https://doi.org/10.1109/PAEP49887.2020.9240911.

11. Velásquez R.M.A., Lara J.V.M. Principal Components Analysis and Adaptive Decision System Based on Fuzzy Logic for Power Transformer. *Fuzzy Information and Engineering*, 2017, vol. 9, no. 4, pp. 493-514. doi: https://doi.org/10.1016/j.fiae.2017.12.005.

12. Gouda O.E., Saleh S.M., Hamdy EL-Hoshy S. Power Transformer Incipient Faults Diagnosis Based on Dissolved Gas Analysis. *TELKOMNIKA Indonesian Journal of Electrical Engineering*, 2015, vol. 16, no. 3, pp. 409-416. doi: https://doi.org/10.11591/tijee.v16i3.1630.

13. Faiz J., Soleimani M. Dissolved gas analysis evaluation in electric power transformers using conventional methods a review. *IEEE Transactions on Dielectrics and Electrical Insulation*, 2017, vol. 24, no. 2, pp. 1239-1248. doi: https://doi.org/10.1109/TDEI.2017.005959.

14. Castro A.R.G., Miranda V. An interpretation of neural networks as inference engines with application to transformer failure diagnosis. *International Journal of Electrical Power & Energy Systems*, 2005, vol. 27, no. 9–10, pp. 620-626. doi: https://doi.org/10.1016/j.ijepes.2005.08.002.

15. Taha I.B.M., Ghoneim S.S.M., Duaywah A.S.A. Refining DGA methods of IEC Code and Rogers four ratios for transformer fault diagnosis. *2016 IEEE Power and Energy Society General Meeting (PESGM)*, 2016, pp. 1-5. doi: https://doi.org/10.1109/PESGM.2016.7741157.

16. Li Z., Jiao Z., He A. Knowledge-based artificial neural network for power transformer protection. *IET Generation, Transmission & Distribution*, 2020, vol. 14, no. 24, pp. 5782-5791. doi: https://doi.org/10.1049/iet-gtd.2020.0542.

17. Bondarenko V.E., Shutenko O.V. Development of fuzzy neural network for the interpretation of the results of dissolved in oil gases analysis. *Electrical Engineering & Electromechanics*, 2017, no. 2, pp. 49-56. doi: https://doi.org/10.20998/2074-272X.2017.2.08.

18. Yang H., Zhang Z., Yin X. A novel method of decision-making for power transformer maintenance based on failure-probability-analysis. *IEEJ Transactions on Electrical and Electronic Engineering*, 2018, vol. 13, no. 5, pp. 689-695. doi: https://doi.org/10.1002/tee.22618.

19. Faiz J., Soleimani M. Assessment of computational intelligence and conventional dissolved gas analysis methods for transformer fault diagnosis. *IEEE Transactions on Dielectrics and Electrical Insulation*, 2018, vol. 25, no. 5, pp. 1798-1806. doi: https://doi.org/10.1109/TDEI.2018.007191.

20. Wang B., Li Y., Watada J. A New MOPSO to Solve a Multi-Objective Portfolio Selection Model with Fuzzy Value-at-Risk. *Lecture Notes in Computer Science*, 2011, vol. 6883, pp. 217-226. doi: https://doi.org/10.1007/978-3-642-23854-3_23.

21. Tran Q.T., Davies K., Roose L., Wiriyakitikun P., Janjampop J., Riva Sanseverino E., Zizzo G. A Review of Health Assessment Techniques for Distribution Transformers in Smart Distribution Grids. *Applied Sciences*, 2020, vol. 10, no. 22, atr. no. 8115. doi: https://doi.org/10.3390/app10228115.

22. Das S., Guha D. A Centroid-based Ranking Method of Trapezoidal Intuitionistic Fuzzy Numbers and Its Application to MCDM Problems. *Fuzzy Information and Engineering*, 2016, vol. 8, no. 1, pp. 41-74. doi: https://doi.org/10.1016/j.fiae.2016.03.004.

23. Abu-Elanien A.E.B., Salama M.M.A., Ibrahim M. Calculation of a Health Index for Oil-Immersed Transformers Rated Under 69 kV Using Fuzzy Logic. *IEEE Transactions on Power Delivery*, 2012, vol. 27, no. 4, pp. 2029-2036. doi: https://doi.org/10.1109/TPWRD.2012.2205165.

24. Javier Quispe Carita A., Cambraia Leite L., Pedro Pires Medeiros A., Barros R., Sauer L. Bayesian Networks applied to Failure Diagnosis in Power Transformer. *IEEE Latin America Transactions*, 2013, vol. 11, no. 4, pp. 1075-1082. doi: https://doi.org/10.1109/TLA.2013.6601752.
25. Tang W.H., Spurgeon K., Wu Q.H., Richardson Z.J. An evidential reasoning approach to transformer condition assessments. *IEEE Transactions on Power Delivery*, 2004, vol. 19, no. 4, pp. 1696-1703. doi: https://doi.org/10.1109/TPWRD.2003.822542.
26. Ma H., Ekanayake C., Saha T.K. Power transformer fault diagnosis under measurement originated uncertainties. *IEEE Transactions on Dielectrics and Electrical Insulation*, 2012, vol. 19, no. 6, pp. 1982-1990. doi: https://doi.org/10.1109/TDEI.2012.6396956.
27. Miranda V., Castro A.R.G., Lima S. Diagnosing Faults in Power Transformers With Autoassociative Neural Networks and Mean Shift. *IEEE Transactions on Power Delivery*, 2012, vol. 27, no. 3, pp. 1350-1357. doi: https://doi.org/10.1109/TPWRD.2012.2188143.
28. Shirai Y., Noda S., Yamabe K., Hattori K., Baba J., Nishihara T., Nitta T., Kobayashi S., Sato K. Current Limiting Performance of Three-Phase Concentric Transformer Type SFCL at Unbalanced Fault Conditions. *IEEE Transactions on Applied Superconductivity*, 2013, vol. 23, no. 3, pp. 5601905-5601905. doi: https://doi.org/10.1109/TASC.2012.2233533.
29. Li Lixiang. Research and application on Set Pair Analysis for E-government comprehensive evaluation model. *2010 3rd International Conference on Advanced Computer Theory and Engineering (ICACTE)*, 2010, pp. V1-70-V1-74. doi: https://doi.org/10.1109/ICACTE.2010.5579062.
30. Gao H., Sun Y., Li K., Zhou Q., Liu G., Ge H. An insulation condition assessment method of transformer based on set pair analysis and similarity clustering. *2016 IEEE 11th Conference on Industrial Electronics and Applications (ICIEA)*, 2016, pp. 43-48. doi: https://doi.org/10.1109/ICIEA.2016.7603549.
31. Niederberger M., Spranger J. Delphi Technique in Health Sciences: A Map. *Frontiers in Public Health*, 2020, vol. 8, pp. 457-467. doi: https://doi.org/10.3389/fpubh.2020.00457.
32. Bardyk E., Bolotnyi N. Parametric identification of fuzzy model for power transformer based on real operation data. *Eastern-European Journal of Enterprise Technologies*, 2017, vol. 6, no. 8(90), pp. 4-10. doi: https://doi.org/10.15587/1729-4061.2017.118632.
33. Bardyk Ye.I. Modelling and assessment of chances of failure of power systems electrical equipment taking into account the after repair resource restoration level. *Naukovyi Visnyk Natsionalnoho Hirnychoho Universytetu*, 2014, no. 3, pp. 82-90.
34. Bardyk E.I., Bolotnyi N. An Analysis of Uncertainty for Failure Risk Assessment of Power Transformer. *2022 IEEE 8th International Conference on Energy Smart Systems (ESS)*, 2022, pp. 31-35. doi: https://doi.org/10.1109/ESS57819.2022.9969341.
35. Bardyk E.I., Bolotnyi N. Improved Power Transformer Condition Assessment under Uncertainty using Fuzzy Logic. *2022 IEEE 8th International Conference on Energy Smart Systems (ESS)*, 2022, pp. 53-58. doi: https://doi.org/10.1109/ESS57819.2022.9969327.
36. Bardyk E., Bolotnyi N. Development of a mathematical model for cost distribution of maintenance and repair of electrical equipment. *Eastern-European Journal of Enterprise Technologies*, 2018, vol. 6, no. 8(96), pp. 6-16. doi: https://doi.org/10.15587/1729-4061.2018.147622.

Received 28.10.2022
Accepted 24.01.2023
Published 01.09.2023

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How to cite this article:
Bardyk E.I., Bolotnyi N.P. Development of fuzzy classifier for technical condition ranking of power transformer. *Electrical Engineering & Electromechanics*, 2023, no. 5, pp. 3-13. doi: https://doi.org/10.20998/2074-272X.2023.5.01