Розроблено математичну модель оцінки технічного стану силового трансформатора на основі нечіткої логіки. Запропоновано метод нелінійної оптимізації для налаштування параметрів моделі, який підвищує точність нечіткого моделювання оцінки технічного стану силового трансформатора. Проведено адаптацію нечіткої моделі до реальних умов експлуатації і виконано порівняльний аналіз результатів нечіткого моделювання оцінки технічного стану силового трансформатора

Ключові слова: силовий трансформатор, хроматографічний аналіз розчиненого газу (ХАРГ), оцінка технічного стану, нечітка модель, функція належності

Разработана математическая модель оценки технического состояния силового трансформатора на основе нечеткой логики. Предложен метод нелинейной оптимизации для настройки параметров модели, который повышает точность нечеткого моделирования оценки технического состояния силового трансформатора. Проведена адаптация нечеткой модели к реальным условиям эксплуатации и выполнен сравнительный анализ результатов нечеткого моделирования оценки технического состояния силового трансформатора

Ключевые слова: силовой трансформатор, хроматографический анализ растворенного газа (ХАРГ), оценка технического состояния, нечеткая модель, функция принадлежности

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PARAMETRIC IDENTIFICATION OF FUZZY MODEL FOR POWER TRANSFORMER BASED ON REAL OPERATION DATA

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1. Introduction

The analysis of operating conditions of modern power systems shows a steady increase in the accident rate [1]. This is primarily due to an increase in the share of electrical equipment failures, low rates of replacement, complicated weather conditions and working conditions of operational personnel. In this connection, the problem of increasing the power system reliability due to an objective assessment of technical condition and failure risk of electrical equipment is of great importance.

Power transformers are one of the most critical and costly elements of modern power systems. According to the viewed literature, a power transformer is expected to operate satisfactorily up to 40–45 years [2–5]. The increase in the share of power transformers with a lifetime of more than 25–30 years exacerbates the problem of ensuring an objective assessment of technical condition and operation risk determination of electric power systems.

The oil-cellulose insulation in power transformers will continue aging over a lifetime and cannot be replaced. The aging of oil-immersed cellulose insulation decreases the mechanical strength and further limits the transformer operation [6].

Statistical data show that most of the transformer damage is related to the insulation system failure while the cellulose insulation life is equal to the transformer life. Power transformer failures are commonly caused by events such as a short circuit or a lightning strike. Due to transformer aging, the mechanical strength of paper insulation will decrease and short circuit events like this can cause the ultimate transformer failure. Because of their random occurrence, we cannot be certain when the final transformer failure is going to happen. However, if the strength of the latest paper insulation is known, it is possible to make an estimation of when these events might occur [7].

At the same time, the practice of electrical equipment operation of electric power systems shows that there is only limited statistical information. Today the registration and processing of damage data, which are detected during repairs are not sufficiently systematized, since certain damages that occur during the operation are not always detected.

Total technical condition assessment of power transformers usually involves aggregating the state of the following individual elements: winding, magnetic core, solid insulation, high-voltage bushings, load tap changer, etc.

The problem of complexity of technical condition assessment and service life prediction is determined by the measurement frequency, but power transformers are not always equipped with appropriate monitoring systems.

In addition, the criteria values of technical condition parameters separating one power transformer from another are often obtained on the basis of limited statistical data and subjective information of repair from maintenance personnel.

In this regard, the development of mathematical models for diagnosing the technical condition of power transformers and adapting to real operation conditions in power systems is an actual problem.

2. Literature review and problem statement

Different methods of diagnosis have been used to assess the insulation degradation rate, i. e., dissolved gas analysis (DGA) and the aging estimation based on loading history.

DGA has been proved a well known diagnostic technique for the early detection of transformers incipient faults. The DGA test is performed yearly on transformers according to the standard method [8]. Detection of dissolved gases in transformers oil during its service is the first indication of malfunctioning and finally leads to the transformers failure.

From the DGA, it is possible to recommend further testing and maintenance activities on the faulty transformers. Possible mechanisms for gas generation in the transformer oil may be arcing, partial discharge, low energy discharge, overheating of insulation due to severe overloading, failure of forced cooling systems, etc.

Analyses of dissolved gases generated in transformers oil are used for qualitative determination of the fault type. This is usually based on existing gas, which is typical or predominant at various temperatures. Different DGA methods are used by various power utilities to assess the transformer oil condition. To improve and standardize the DGA, several diagnostic criteria have been proposed such as IEC/IEEE ratio methods, Rogers ratios [8], key gas, Dornenburg ratios, modified Rogers ratios [9] and Duval triangle [10], which have been developed by researchers [8–12].

Recently, online monitoring of power transformers has become popular because of the development of artificial intelligent systems [11]. For example, ANFIS has been used as an estimator in several studies for many purposes. For the transformer diagnosis purposes, various studies report the successful use of ANFIS to do the DGA and complement the existing methods as shown in [12].

Table 1 presents the results of some systems developed for the transformer diagnosis based on the DGA analysis. The quantitative indicators of the diagnostic accuracy of the presented systems reflect the necessity of using the methods that minimize the error of technical condition assessment of power transformers [13–17].

In [18], a review of the fuzzy-logic method is proposed for the power transformer fault diagnosis based on the DGA test. This review shows that various fuzzy-logic techniques for the power transformer fault detection have been developed in order to reduce operating costs, enhance operational reliability and improve power and services of customers [19]. The disadvantages of fuzzy-logic methods [20] are that membership functions must be determined according to practical experience or expert advice, operational conditions that are not always taken into account in fuzzy simulation. The inaccuracies are always associated with the DGA tests, which may affect the gas ratios, concentrations differences, and other calculations. Therefore, there is a need to improve the fuzzy model of technical condition assessment of power transformers by adjusting the membership function parameters based on the use of operational data obtained on existing power transformers.

Table 1

The results for some fault diagnosis systems of power transformers

Number of samples in dataset	Diagnosis accuracy of developed systems, (%)	Reference
711	90.3 – training dataset 93.81 – testing dataset	[13]
210	95.72 – training dataset 95.34 – testing dataset	[14]
711	96.2	[15]
33	90. 91 – Dornenburg ratios 87. 88 – modified Rogers ratios 90. 91 – Rogers ratios 93. 94 – IEC/IEEE ratio	[16]
820	90.49 – training dataset 93.54 – testing dataset	[17]

3. The aim and objectives of the study

The aim of the present research is to develop the model of technical condition assessment of power transformers using the method, which would help to adapt the model to real operation conditions of power transformers of electric power systems.

To achieve this goal, the following tasks were set:

– to perform the structural identification of the fuzzy model of technical condition assessment of power transformers based on the DGA test results obtained by measuring the absolute gas concentration in transformer oil;

– to carry out the parametric identification of the fuzzy model by setting the membership function parameters on the basis of the nonlinear optimization method.

4. Materials and methods for model development of technical condition diagnostics of power transformers

4. 1. Experimental research base

The study was carried out using the statistical information about failures and DGA test results from functioning power transformers, which were provided by the Ukraine's power grid.

4. 2. Fuzzy model for technical condition diagnostics of power transformers

The fuzzy mathematical model was developed to determine the technical condition of power oil transformers based on the results of individual tests. It contains fuzzy inference rules, the term-set and membership functions of input parameters to one or another linguistic value.

The knowledge base of the expert system prototype for the diagnostics of technical condition of power transformers is based on a hierarchical representation and consists of a system of embedded knowledge bases.

The integral assessment of technical condition is carried out by aggregating the findings on the type of power transformer fault by individual test results using appropriate knowledge bases.

The fuzzy model for the diagnostics of technical condition of power transformers allows identifying the following major faults: low and high energy partial discharges; low and high energy discharges; low, medium and high thermal temperature faults; assessment of the solid-state insulation; evaluation of the mechanical state of windings, etc.

The hierarchical block diagram (Fig. 1) of the developed model and the algorithm of fuzzy inference about the technical condition of power oil transformers are described in detail [21].

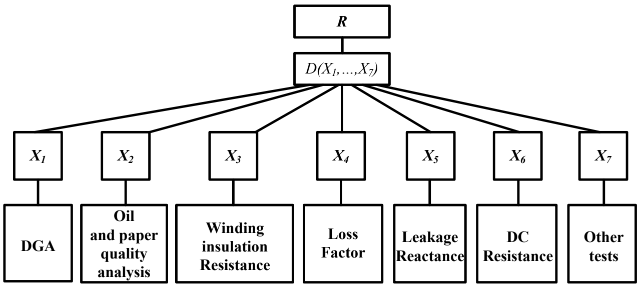

Fig. 1. The hierarchical block diagram for the technical condition assessment of power transformers

In the world practice of power companies, the DGA in oil is used as the main type of diagnostics, which revealed most faults and it is now used as the basic method for evaluating the technical condition of power transformers [22]. However, the problem of interpreting the DGA results is complicated, since it is not always possible to detect damage in power transformers [23].

Fuzzy logic is particularly effective for interpreting the results of the DGA and other tests [24]. It is based on fuzzy evaluation criteria to more precisely determine the technical condition of power transformers [25].

The fuzzy expert system to assess the technical condition of power transformers by the DGA test results was presented [26]. The Sugeno-type fuzzy inference system (FIS) is used for this purpose.

The fuzzy logic analysis involves three successive processes, namely: fuzzification, fuzzy inference and defuzzification. Fuzzification converts a crisp gas ratio into a fuzzy input membership. A chosen FIS is responsible for obtaining conclusions from the knowledge-based fuzzy rules set of "if – then" linguistic statements. Defuzzification then converts the output values back into the crisp values.

The inputs of the FIS are linguistic variables of gas concentration ratios C_i (i=1…3), which have the following term sets:

$$C_1=\{T_L^1,T_M^1,T_H^1\}\rightarrow \mathrm{C_2H_2/C_2H_4},$$

$$C_2=\{T_L^2,T_M^2,T_H^2\}\rightarrow \mathrm{CH_4/H_2},$$

$$C_3=\{T_L^3,T_M^3,T_H^3\}\rightarrow \mathrm{C_2H_4/C_2H_6},$$

where T_L^i, T_M^i, T_H^i are "low", "medium", "high" values of the i-th parameter.

All inputs of the fuzzy logic system have 3 membership functions, the basic forms and parameters of which are presented in Fig. 2, respectively.

To account for the objectively existing tolerance of recognizable damage before changing the gas concentration ratios in a certain range (for example, from [0,1 ... 3] for C_1), the trapezoidal membership functions were used.

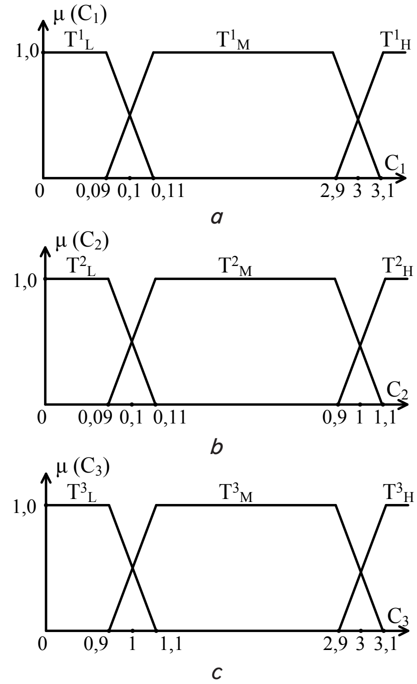

Fig. 2. Membership functions:
a — input variable of C_2H_2/C_2H_4; *b* — input variable of CH_4/H_2; *c* — input variable of C_2H_4/C_2H_6

These inputs are given to the FIS for obtaining the output. Based on the IEEE Standard [27], the data and 9 fuzzy inference rules for multiple faults are suggested in Table 2.

Table 2

Schematic diagnostic codes of the fuzzy system

Ratios of characteristic gases			Characteristic fault type	Fault code set
$\frac{C_2H_2}{C_2H_4}$	$\frac{CH_4}{H_2}$	$\frac{C_2H_4}{C_2H_6}$		
T_L^1	T_M^2,T_H^2	T_L^3	Normal	D_1
T_L^1	T_L^2	T_L^3	Low energy partial discharges	D_2
T_M^1	T_L^2	T_L^3	High energy partial discharges	D_3
T_M^1,T_H^1	T_M^2,T_H^2	T_M^3,T_H^3	Low energy discharges	D_4
T_M^1	T_M^2,T_H^2	T_H^3	High energy discharges	D_5
T_L^1	T_M^2,T_H^2	T_M^3	Low temperature thermal fault t<150 °C	D_6
T_L^1	T_H^2	T_L^3	Low temperature thermal fault t<300 °C	D_7
T_L^1	T_H^2	T_M^3	Medium temperature thermal fault T=300–700 °C	D_8
T_L^1	T_H^2	T_H^3	High temperature thermal fault t>700 °C	D_9

Each rule consists of two components, – antecedent (IF part) and consequent (THEN part).With the fuzzy logic technique, the partial membership may improve the number of matched cases as compared to the ordinary crisp theory.

For example, if C_2H_2/C_2H_4 is "low", CH_4/H_2 is "high" and C_2H_4/C_2H_6 is also "low", then the fault type corresponding to this combination of the ratios is D_7, i. e. low temperature thermal fault (overheating) t<300 °C.

4. 3. Adaptation of fuzzy models of technical condition of power transformers to real operation

The criteria values of the parameters (Table 2) used in the fuzzy model are statistically average for a large set of operated power transformers. The actual operating conditions of each particular power transformer may differ from the regulated ones. This requires adaptation of fuzzy models to real operating conditions by setting their parameters.

Setting up a fuzzy model is to find such parameters that minimize deviations between the desired and actual model behavior.

Let the fuzzy model of the technical condition assessment of power transformers $y=f(x_1, x_2, ..., x_n)$ be determined by the expression

$$y=F(X, B, C, W),$$

where $X=(x_1, x_2, ..., x_n)$ is the input vector of the fuzzy model; $B=(b_1, b_2, ..., b_q)$ is the vector of membership function parameters of the fuzzy model; $C=(c_1, c_2, ..., c_q)$ is the vector of fuzzy term parameters from the fuzzy model knowledge base; $W=(w_1, w_2, ..., w_n)$ is the vector of weight coefficients of fuzzy rules; N is the total number of fuzzy rules in the fuzzy model knowledge base; q is the total number of fuzzy model terms; F is the "input-output" operator of the fuzzy model.

The problem of setting up a fuzzy model is performed by optimizing the vector (B, C, W)

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

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

36 parameters of the developed fuzzy model were adjusted in the training, namely: 12 coefficients of the membership functions of term-sets "low" (L), "medium" (M), "high" (H) of input linguistic variables "C_2H_2/C_2H_4, CH_4/H_2, C_2H_4/C_2H_6", where C_2H_2, C_2H_4, CH_4, C_2H_6 are acetylene, ethylene, methane, ethane, respectively.

825 samples of the DGA test results, provided by the Ukraine's power grid were used to evaluate the proposed method. Some of the data samples are given in Table 3. These DGA samples included 50 power transformers with different ratings, voltage levels, operating conditions, age, and loading history, etc., operating all over Ukraine.

Table 3

Training data of the DGA test results

No.	$\frac{C_2H_2}{C_2H_4}$	$\frac{CH_4}{H_2}$	$\frac{C_2H_4}{C_2H_6}$	Fault code
1	0.01	0.117	0.269	D_1
2	0.033	0.156	1.084	D_6
3	0.125	0.1	4.023	D_5
...	...	...	...	...
825	0.005	1.0	4.01	D_9

The parametric identification of optimal values of the membership functions was performed in the MatLab software using the non-linear optimization method presented in Optimization Toolbox [28]. Views of the membership functions after adjusting on the training data are presented in Fig. 3–5.

The obtained results after training the parameters of the membership functions by the DGA test results are presented in Table 4.

Table 4

Simulation results of parametric identification of optimal values of membership functions

Linguistic variable	Term set	Parameters of membership functions							
		Initial value				After training			
		a	b	c	d	a	b	c	d
$\frac{C_2H_2}{C_2H_4}$	T_L^1	0	0	0.09	0.11	0	0	0.0917	0.1028
	T_M^1	0.09	0.11	2.9	3.1	0.0973	0.1116	2.8971	2.9745
	T_H^1	2.9	3.1	1000	1000	2.8997	3.0548	754	754
$\frac{CH_4}{H_2}$	T_L^2	0	0	0.09	0.11	0	0	0.0947	0.1119
	T_M^2	0.09	0.11	0.9	1.1	0.0989	0.1135	0.8947	1.0442
	T_H^2	0.9	1.1	1000	1000	0.9332	1.093	995	995
$\frac{C_2H_4}{C_2H_6}$	T_L^3	0	0	0.09	0.11	0	0	0.8997	0.10793
	T_M^3	0.09	0.11	2.9	3.1	0.9111	0.10997	2.8679	2.9977
	T_H^3	2.9	3.1	1000	1000	2.8993	3.0698	925	925

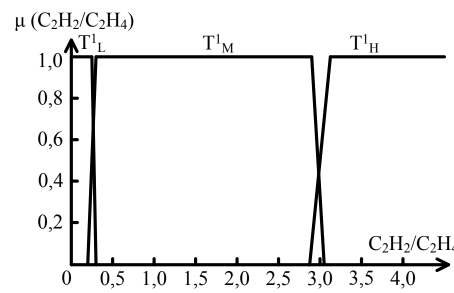

Fig. 3. Membership function of term sets of the input linguistic variable C_2H_2/C_2H_4 after training

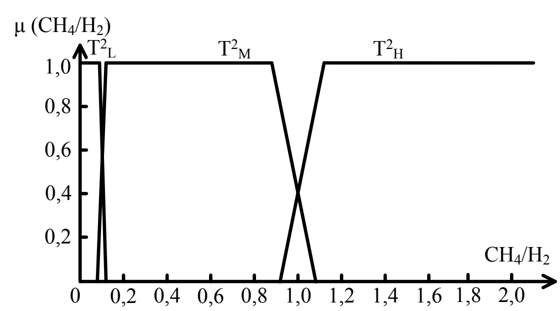

Fig. 4. Membership function of term sets of the input linguistic variable CH_4/H_2 after training

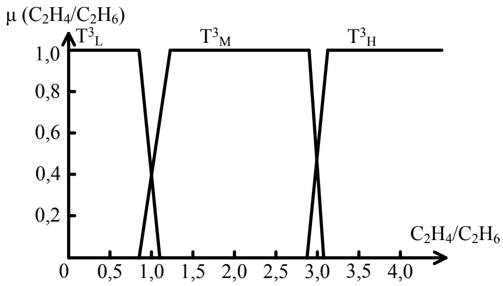

Fig. 5. Membership function of term-sets of the input linguistic variable C_2H_4/C_2H_6 after training

The obtained results of parametric identification of optimal values of the membership functions confirm the effectiveness of the non-linear optimization method. The mean square error of the model identification on the test data R is 1.97.

5. The results of the research on differences in the methods of the technical condition assessment of power transformers

7 DGA samples with clear inference were presented from the transformer oil chromatographic detection records investigated from multiple power supply companies.

After training of the fuzzy model, its performance is analyzed by using the test data shown in Table 5. The comparison of the fuzzy model results with the actual fault justifies the high efficiency and fault identification accuracy of the proposed system (Table 6).

The proposed model is valid and reliable to evaluate the overall condition with uncertainty and incomplete information.

Table 5

The results of the technical condition assessment of power transformers on the testing dataset

Fault types	Number of DGA test samples	Successful identification	Efficiency (%)
Normal	24	24	100
Low energy partial discharges	21	20	95.24
High energy partial discharges	22	20	90.09
Low energy discharges	20	19	95.0
High energy discharges	23	23	100
Low temperature thermal fault t<300 °C	26	25	96.15
Medium temperature thermal fault t=300–700 °C	20	20	100.0
High temperature thermal fault t>700 °C	19	19	100.0

The diagnostic comparison of the proposed method for the technical condition estimation with the conventional method is presented in Table 7.

Table 6

Comparative analysis of the results of the technical condition assessment of power transformers by different methods

No.	Type of power transformer	IEC Standard 60599	Fuzzy Model
1	TDTsG-400-MVA, 330 kV	High temperature thermal fault t>700 °C	High temperature thermal fault t>700 °C, μ(D)=1.00
2	TDTsG-10 MVA, 110 kV	Not identified	Low energy discharges μ(D)=0.6
3	TRDTsG-63 MVA, 110 kV	Medium temperature thermal fault t=300–700 °C	Low temperature thermal fault t=150–300 °C, μ(D)=0.24; Medium temperature thermal fault t=300–700 °C, μ(D)=0.76
4	ATDTsTG-250 MVA, 500 kV	High temperature thermal fault t>700 °C	High temperature thermal fault t>700 °C, μ(D)=1.00
5	TDTG-40 MVA, 110 kV	High temperature thermal fault t>700 °C	High temperature thermal fault t>700 °C, μ(D)=1.00
6	TDTG-63 MVA, 110 kV	Not identified	High energy discharges μ(D)=1.00
7	TDTs-400 MVA, 330 kV	Not identified	High energy discharges μ(D)=0.1

Table 7

Comparison of diagnostic accuracy of fuzzy and conventional methods.

Test dataset	IEC Standard 60599 Accuracy, (%)	Fuzzy Logic Accuracy, (%)
1	79.00	97.12
2	77.20	97.02

The Sugeno-type FIS has an advantage that it can be integrated with optimization techniques so that the FIS can adapt to individual transformers on a case by case basis by making the system self-learning.

The diagnostic accuracy of the technical condition assessment of power transformers on two different test datasets for the fuzzy method is higher compared to the traditional method.

6. Discussion of the results of the research on the accuracy of the methods of the technical condition assessment of power transformers

The necessity of improvement of existing models for the diagnostics of technical condition of power transformers based on the DGA by setting the membership functions parameters is substantiated.

The proposed optimization method as evidenced by the study in Table 5 significantly minimizes the error of the technical condition assessment of power transformers. The presented result is achieved by refining the criteria values of the membership functions of the developed model on the basis of adaptation to real operation data for power transformers operating in one energy zone.

The results obtained in Table 6 show that the FIS has a good efficiency in fault classification after adjustment by refining the boundaries of fault classes which are formed by the criteria values of the membership functions. The developed fuzzy model identifies possible damage for the entire dataset as compared to the traditional method, which did not identify the existing damage for 3 power transformers.

The diagnostic accuracy of the technical condition assessment of power transformers by fuzzy simulation is higher than the estimation by the conventional method and it is equal to 97 % as shown in Table 7.

The advantages of the presented model and method are realized in the complex software "RISK-EPS-NPP" developed by the authors for the operation reliability assessment and risk management of subsystems of electric power systems with NPPs, TPPs and HPPs.

Assessment of technical condition and failure probability of power transformers allows us to quantitatively determine the subsystem state of electric power systems and estimate the losses under blackout of consumers' power supply [29].

The obtained information regarding the possible subsystem state of electric power systems is the basis for developing an algorithm for making efficient decisions about the operation strategy of power transformers and preventive control of the subsystem operation of electric power systems.

For further research, it is necessary to accumulate information about models of the technical condition assessment of power transformers with more objects in different regions of the power grid. This obviously requires the mobilization of significant organizational and technical measures with power supply companies. The results can be implemented at power plants and power supply companies.

7. Conclusions

1. The structure of the fuzzy model of the technical condition assessment of power transformers based on the DGA test results obtained by measuring the absolute gas concentration in transformer oil was developed.

2. The setting procedure of the developed model parameters based on the nonlinear optimization method by the way of optimal values determination of membership functions of fuzzy terms of linguistic variables for the fuzzy model parameters was carried out. A comparison of the fuzzy simulation results for the proposed approach and traditional method with the obtained results of fault diagnostics in operating power transformers is performed. The fault diagnostic accuracy is 97 % and confirms the acceptable efficiency of the adapted fuzzy model for the technical condition assessment of power transformers. The developed mathematical model can be used both in online and offline fault diagnostics of power transformers.

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