International Journal of Electrical and Computer Engineering (IJECE)
Vol. 12, No. 2, April 2022, pp. 1123~1130
ISSN: 2088-8708, DOI: 10.11591/ijece.v12i2.pp1123-1130

An innovative method of fault detection in power transformers

Vladimir Mikhailovich Levin[1], Ammar Abdulazeez Yahya[1,2]
[1]Department of Energy, Novosibirsk State Technical University, Novosibirsk, Russia
[2]Engineering Projects Department, University of Technology, Baghdad, Iraq

Article Info

Article history:

Received Feb 22, 2021
Revised Nov 3, 2021
Accepted Nov 18, 2021

Keywords:

Bayesian classifier
Controllable parameters
Decision rule
Power transformer
Reliability of defect recognition
Statistical calculations
The dichotomy of states classes

ABSTRACT

The Bayesian classifier is a priori the optimal solution for minimizing the total error in problems of statistical pattern recognition. The article suggests using the classifier as a regular tool to increase the reliability of defect recognition in power oil-filled transformers based on the results of the analysis of gases dissolved in oil. The wide application of the Bayesian method for solving tasks of technical diagnostics of electrical equipment is limited by the problem of the multidimensional distribution of random parameters (features) and the nonlinearity of classification. The application of a generalized feature of a defect in the form of a nonlinear function of the transformer state parameters is proposed. This simultaneously reduces the dimension of the initial space of the controlled parameters and significantly improves the stochastic properties of the random distribution of the generalized feature. A special algorithm has been developed to perform statistical calculations and the procedure for recognizing the current technical condition of the transformer using the generated decision rule. The presented research results illustrate the possibility of the practical application of the developed method in the conditions of real operation of power transformers.

Corresponding Author:

Ammar Abdulazeez Yahya
Department of Energy, Novosibirsk State Technical University
20 Karl Marx avenue, Novosibirsk Oblast 630073, Novosibirsk, Russia
Email: ammarazez384@gmail.com

1. INTRODUCTION

Numerous studies and research have been devoted to increasing the reliability of diagnosing and evaluating the technical condition of power transformers. Increasing the reliability (reducing the error) of the equipment condition assessment is one of the key tasks of technical diagnostics, regardless of the scope of application, the methods, and the diagnostic tools used. The urgency of the problem is associated with the severity of the consequences (costs, damage) that arise as a result of errors in the diagnosis, based on which untimely and unjustified decisions are made to withdraw equipment for repair or refuse to repair. Numerous studies have been devoted to solving this problem, the results of which are particularly reflected in the following publications [1]–[5].

The reliability of diagnostics is usually understood as a numerical characteristic of the correspondence of the diagnostic results to the actual technical condition of the object [3]. It is customary to distinguish between instrumental and methodical reliability of diagnosis [1]. Instrumental reliability is determined by the composition and stability of the object's diagnostic parameters, the specified tolerances, as well as the accuracy, sensitivity, and condition of the measuring instruments [4], [5]. Methodical reliability, as a rule, is associated with the processing of measurement results, the choice of diagnostic features, and criteria for assessing the technical condition of the equipment [6]–[9].

One of the promising directions for improving the methodical reliability of diagnosing oil-filled power transformers using the results of various control methods is the use of statistical solutions based on the processing of multi-parameter measurement data [10]–[14]. Methods for transformers diagnosing have different frequencies of application, sensitivity to the occurrence of malfunctions, and, as a result, different information content in terms of statistical estimates. The most informative methods include methods for early detection of developing defects in transformer equipment, such as analysis of dissolved gases in oil (DGA), vibration diagnostics, and thermal diagnostics. These methods allow generating a representative sample of data for a relatively short period of operation of the equipment, which is a prerequisite for the application of statistical classification.

The Bayes method successfully solves the problems of statistical classification and pattern recognition [15], [16]. The method allows you to adapt the probabilities of the outcomes of random events to the newly emerging a priori information [17], [18]. However, the wide use of the Bayes method for the development of effective practical applications in the diagnosis of transformers is hindered by the multimodality and multidimensionality of statistical distributions of controlled parameters, as well as the nonlinear separability of classes of states [19], [20]. Overcoming these limitations requires a special approach and is an actual task. The article is devoted to the development of a statistical approach in the direction of using the Bayesian classifier as a regular effective tool for improving the methodological reliability of recognizing defects in oil-filled transformer equipment based on the results of DGA. The results of the conducted studies touch upon and discuss aspects of the diagnostic value and stochastic nature of the obtained solutions.

2. THE MAIN THEORETICAL PROVISIONS

The statistical approach to the problems of technical diagnostics of electrical equipment (EE) is based on the presence of a representative sample of experimental data from a certain general totality, which corresponds to a certain distribution law with statistical moments of this distribution. This position made it possible to apply the known methods of statistical analysis to the solution of many fundamentally important diagnostic problems, for example, as the formation of a reliable image of defects, determination of admissible and maximum permissible values of controlled parameters, identification, and formalization of practically significant statistical dependencies [14]–[16].

As a rule, in the operation of EE, the formation of samples of experimental data is preceded by the determination of a set of informative controlled parameters (signs of defects), which will play the role of random variables (RV). The dimension of the initial feature vector $X = \{x_1, x_2, \ldots, x_n\}$ is the parameter on which the reliability of the obtained diagnostic evaluations depends critically. The fact is that each RV X - vector component often has its own statistical distribution with its numerical characteristics, which significantly complicates the integral assessment of the feature vector for the formation and separation of classes of states EE. Reduction of feature space dimensional simplifies transformations and facilitates the solution of the statistical classification problem. To reduce the feature space, methods based on the exclusion of dependent and insignificant components are applicable (factor analysis method, principal component analysis method) which, however, do not eliminate the loss of useful diagnostic information [17], [18].

One of the methods using the reduction of the initial space of the controlled features through a special transformation in the form of a nonlinear function of the primary diagnostic parameters (1) was proposed in [12]. The method used for the DGA of power transformers (PT) introduces a generalized feature D that converts a multidimensional space X of parameters (concentrations of diagnostic gases $\left(A_i,\ ppm,\ i = \overline{1.7}\right)$) into a one-dimensional RV with changes on the numerical axis in the interval $0 \div \infty$):

$$D = \sum_{i=1}^{7} \left[\frac{\left(\frac{A_i}{A_{imax}}\right)^2}{\sum_{i=1}^{7} \left(\frac{A_i}{A_{imax}}\right)} \right] \tag{1}$$

here A_{imax}, ppm - preset limits for the concentration of diagnostic gases.

An adequate replacement of the random vector of gas concentrations $\{A_i\}$ by a scalar discrete RV Dallows moving from a multidimensional problem to the study of the properties of a one-dimensional random distribution. In addition, on the positive axis $D \in 0 \div \infty$) the dichotomy of the PT state classes is distinguished:

Class S_1 state "normal";
Class S_2 state "deviation from the normal (2)

The decisive rule that establishes an unambiguous correspondence between the presence of a developing defect in the PT, the value of a generalized diagnostic feature D, and a set of classes of the technical condition of the equipment can be formed only after determining the boundary of the dichotomy of classes (2). Under conditions of operation of a group of similar PT, a random implementation is obtained based on a single DGA protocol. Taking into account the composition of the PT group and the duration of their operation period (on average 5 years) a representative sample of RV can be formed, which is subjected to statistical analysis to verify the distribution law and calculate the statistical moments in each of the classes of states. To perform the initial differentiation of the dichotomy of state classes, the criterion of "boundary concentrations" [19] is used, according to which:

$$A_i \leq A_{imax} \in \ S_1;\ A_i > A_{imax} \in \ S_2 \tag{3}$$

due to the possibility of starting classification according to criterion (3), two training sets of RV D for the selected dichotomy can be formed.

A statistical analysis of distributions D for each of the classes of states is carried out with the determination of their numerical and integral characteristics, as well as with the testing of the hypothesis of belonging to a certain distribution law. Numerous studies of DGA statistics on different control groups PT 110-220 kV [20], [21] allowed us to identify and justify several characteristic features of the distribution of RV D:

a. In most practical cases, the statistical distributions of RV D in the state classes S_1, S_2 and are mixtures of several homogeneous distributions. If it is possible to separate them, additional diagnostic information appears, which is valuable for substantiating decision-making rules for the further operation of the PT.
b. The width of the range of change of RV D in the class S_1 is due to:
   – The difference in the service life of the PT of the control group: the aging of structural elements gradually increases the concentration of characteristic gases and, as a consequence, the value D;
   – Periodic corrective actions for long-term operating PT: corrective action with oil degassing reduces gas concentrations, with them and the values D, making them comparable with the values characteristic of new PT.
c. The width of the range of RV D changes in class S_2 is primarily due to the varying degrees of criticality (stage of development) of defects detected in PT;
d. As a rule, the RV D distributions in each of the classes are two-parameter and obey one of the laws: normal, log-normal, gamma, which opens up possibilities for applying the significant advantages of the Bayesian classifier when forming the dichotomy interface of classes state PT [20]. One of the invaluable diagnostic evaluations of the merits of the statistical Bayesian classifier based on the likelihood ratio is the possibility of minimizing the total error of defect recognition in the EE [21], [22]. Moreover, along with an assessment of the belonging of the current state of EE to one of the distinguished classes of states, the probability of this assessment can also be determined.

The Bayesian classifier, formed for a given dichotomy of classes S_1 and S_2, satisfying all these requirements, is represented by the expression (4):

$$ln[p(D/S_2)] - ln[p(D/S_1)] = ln\left[\frac{P(S_1)}{P(S_2)}\right] \tag{4}$$

here: $p\left(D/S_j\right)$ - conditional probability density$D$ $\left(j = \overline{1,2}\right)$; $P\left(S_j\right)$ a priori probabilities of the state of the PT belonging to the jth class; $\frac{P(S_1)}{P(S_2)}$ - likelihood ratio. For a random variable D, distributed according to the law normal or close to it, expression (4) is transformed into a quadratic form with a strict analytical solution (5):

$$D_{max} = \frac{\left(M_1 \cdot \sigma_2^2 - M_2 \cdot \sigma_1^2 + \sqrt{R}\right)}{(\sigma_2^2 - \sigma_1^2)} \tag{5}$$

where: D_{max} - mathematical model of the interface between the classes of states of PT; $\sqrt{R}$ - a function of the numerical characteristics of a random attribute in each j class of transformer states (Mj-mathematical expectations; σ_j-standard deviation). In the case of a normal distribution of RV D the approximate mathematical model (6) can be contrasted to the complete interface model of the dichotomy of state classes (5):

$$D_{max} \simeq M_1 + k \cdot \sigma_1 \tag{6}$$

which satisfying the "3-sigma rule" for the normal statistical distribution D in the class of states S_1. Studies have established a fairly good agreement between the results of calculating D_{max} using the exact (5) and approximate (6) models. In addition, model (6) allows you to adjust the D_{max} value by selecting the computational constant $k = 2 \div 3$ according to the criterion $\min[\varepsilon(k)]$, where $\varepsilon(k)$ - the estimate of the total error of defect-recognition in PT, including error estimates of the first and second kind: ε_1 - "false anxiety" and ε_2- "defect skipping". Based on the foregoing, we can formulate the following decision-making rules for recognizing PT operational status classes:

$$D \leq D_{max}, state\ class\ S_1;\ D > D_{max}, state\ class\ S_2 \quad (7)$$

3. CALCULATION RESULTS, ANALYSIS AND DISCUSSION

In the computational part of the study, the situation with one of the block transformer TPS (TDN-250000/220 kV) of 1992 is considered. In August 2006, according to diagnostic data, a developing thermal defect in the high-temperature range $\theta > 700\ °C$ was detected in the transformer. Further operation of the PT was accompanied by an increase in the concentration of hydrocarbon gases: C_2H_4-ethylene, CH_4-methane, C_2H_6-ethane, as well as CO-carbon monoxide and CO_2-carbon dioxide. The center of the defect was presumably located in the lower part of the yoke of the magnetic circuit, where access was excluded without completely disassembling the structure of the active part (that is, performing an expensive overhaul). During the operation, it was decided to continue the operation of the PT under load with a frequent sampling of oil for DGA and its periodic degassing. In this condition, the PT was operated on until March 2013. During this time, the development of the defect has passed into a critical phase with the threat of thermal damage to the cellulose insulation. As a result, the DGA retrospective comprised 146 protocols, of which 57 (by criterion (3)) belonged to the state class S_1, and 89-to the class S_2. Figure 1 shows the relative frequency D histograms for the selected dichotomy of state classes. The area of intersection of the histograms in the classes S_1 and S_2 determines the total error in recognizing the state of the PT, the estimate of which is $\varepsilon = 3.42\%$. The numerous characteristics of the distributions for the class dichotomy are given in Table 1. The D_{max} calculations using models (5) and (6) showed fairly close results of 0.7351 and 0.7347, respectively.

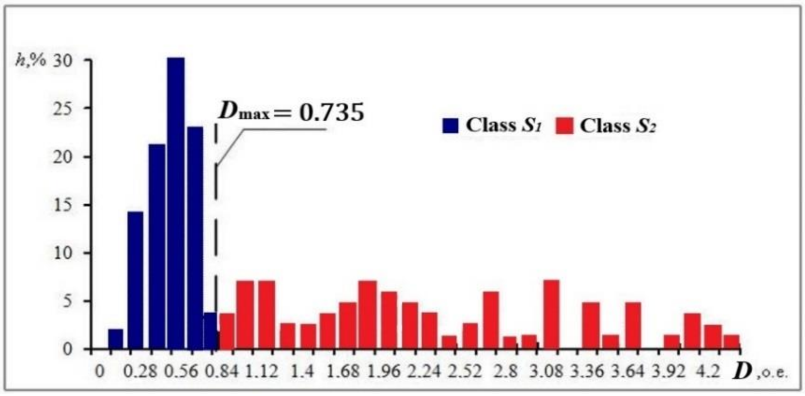


Figure 1. Histograms of relative frequencies RV D for the dichotomy of classes PT

With the value of the computational constant in expression (6) $k = 2$ the following error estimates are determined $\varepsilon_1 = 2.08\%$ and $\varepsilon_2 = 1.34\%$, which is quite acceptable from the point of view of real operational practice. This is quite acceptable from the point of view of real operational practice. Statistical analysis of two-parameter distributions of RV D in each of the classes of PT states with verification of the initial hypothesis of belonging to one of the above laws was carried out using the Kolmogorov-Smirnov criterion [23]–[25]. Calculations with different confidence levels have confirmed the validity of the proposed initial hypothesis. The results of testing hypotheses about the statistical law of distribution of RV is shown in Figure 2(a) normal distribution in class S_1, Figure 2(b) lognormal distribution in class S_2, Figure 2(c) lognormal distribution in class S_1, and Figure 2(d) gamma distribution in class S_2. The results of the study found that with a confidence probability of 0.95, the studied distribution of the random attribute D in the class S_1 satisfies the normal law in the class S_2 it satisfies the log-normal law. When studying the influence of the amount and composition of diagnostic gases (n) dissolved in PT oil on the reliability of the Bayesian classifier model, the following considerations were taken into account:

- Reduction (to the standard set of gases at n=7) the number of monitored gases will, as expected, lead to a decrease in the reliability of the statistical model for recognizing PT states due to the loss of useful information;
- Arbitrariness in the choice of the composition of controlled gases should be limited and based on the physicochemical interpretation of defect formation processes in PT.

Table 1. Numerous characteristics of the distributions RV D for each of the classes of states

Class States PT	The values of the numerical characteristics of the distribution D	
S_1 "normal"	M_1=0.4273	σ_1=0.1537
S_2 "deviation from the normal"	M_2=2.0622	σ_2=1.0689

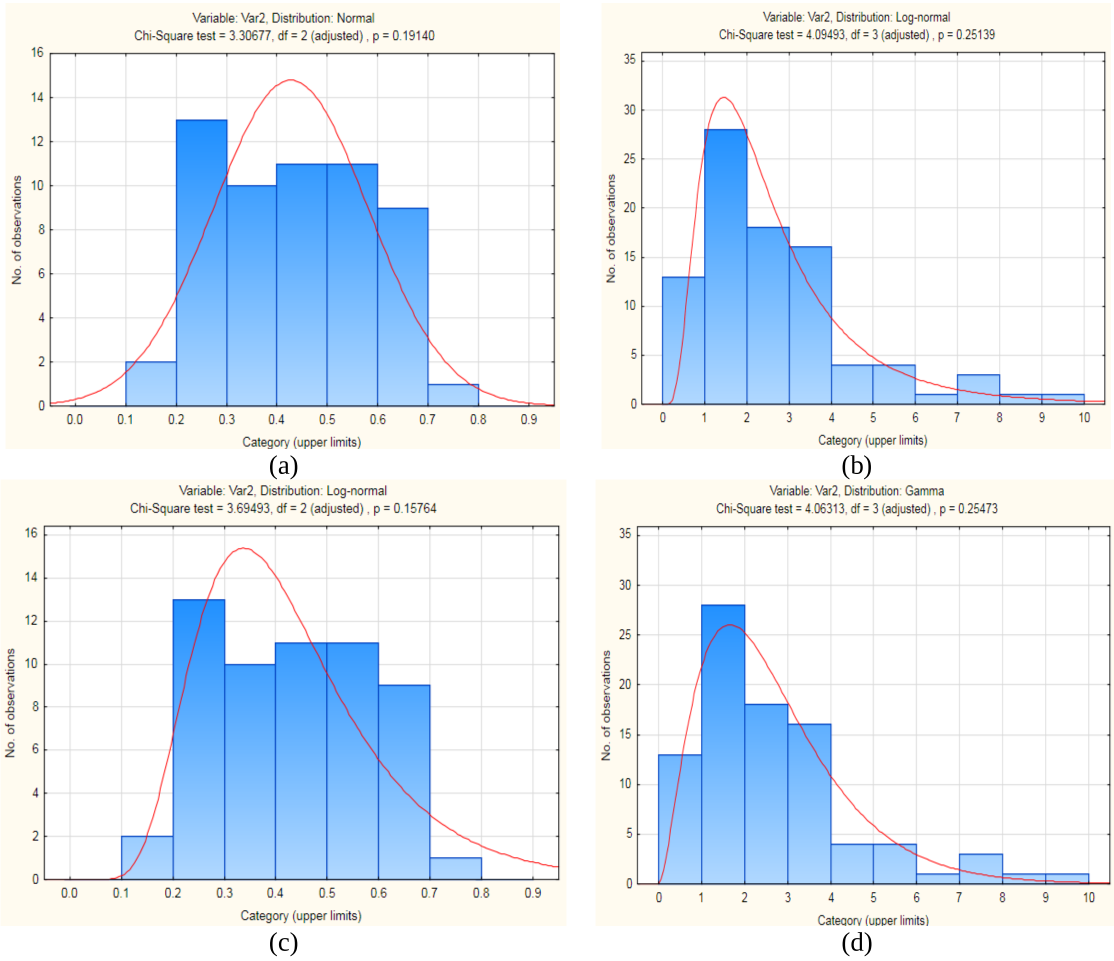
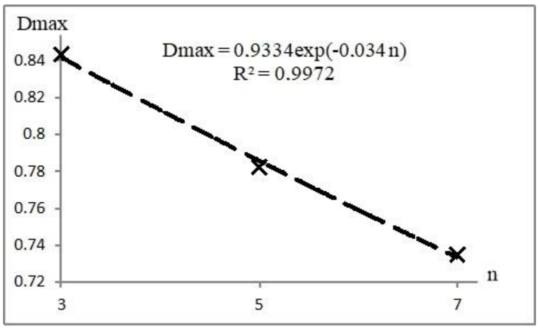


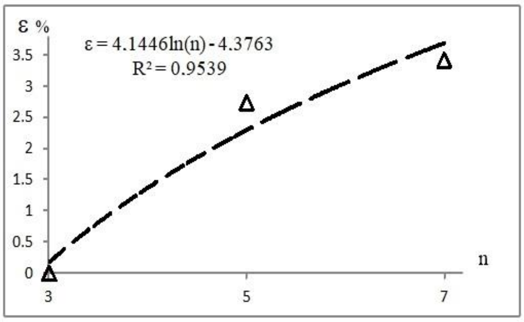
Figure 2. The results of testing hypotheses about the statistical law of distribution of RV: (a) normal distribution in class S_1, (b) lognormal distribution in class S_2, (c) lognormal distribution in class S_1, and (d) gamma distribution in class S_2

Taking into account the above, the reduction in the number of gases to n=5 in the traditional composition, except for carbon oxide and carbon dioxide, is due to the presence of CO, CO_2 and in the PT oil, regardless of the duration of operation and the presence of internal faults and is associated with the chemical composition of the organic dielectric. The reduction in the number of gases to n=3 in the composition of CH_4, C_2H_2, C_2H_4 is due to their status of a "key gas" in poorly classified situations of developing thermal defects in the ranges of low and medium temperatures. In addition, the indicated composition of gases determines the scheme for interpreting defects in PT using the Duval triangle method [26]–[28]. The analysis of the results showed that the reduction in the number of parameters involved in the formation of the Bayesian classification model causes a characteristic change in the statistical moments of the

RV D in the classes of states S_1, S_2 and. So, for example, the mathematical expectation M_1 tends to increase from 0.4273 at n=7, up to 0.4429 at n=3. Similarly, increases the standard deviation σ_1 increases from 0.1537 to 0.2002 and, as a consequence, the value of D_{max}, calculated by expression (6), Figure 3(a) shows decrease D_{max} by increasing the number of parameters n and Figure 3(b) shows that the total classification error increases with increasing number of parameters n. For the automation of statistical calculations and the subsequent diagnostic assessment of the PT state according to the criteria (7), an algorithmic and software implementation is developed as shown in Figure 4.



(a)



(b)

Figure 3. Dependences of the characteristics of the classifier model on the number of controlled gases: (a) boundary between classes of PT states and (b) total classification error according to DGA

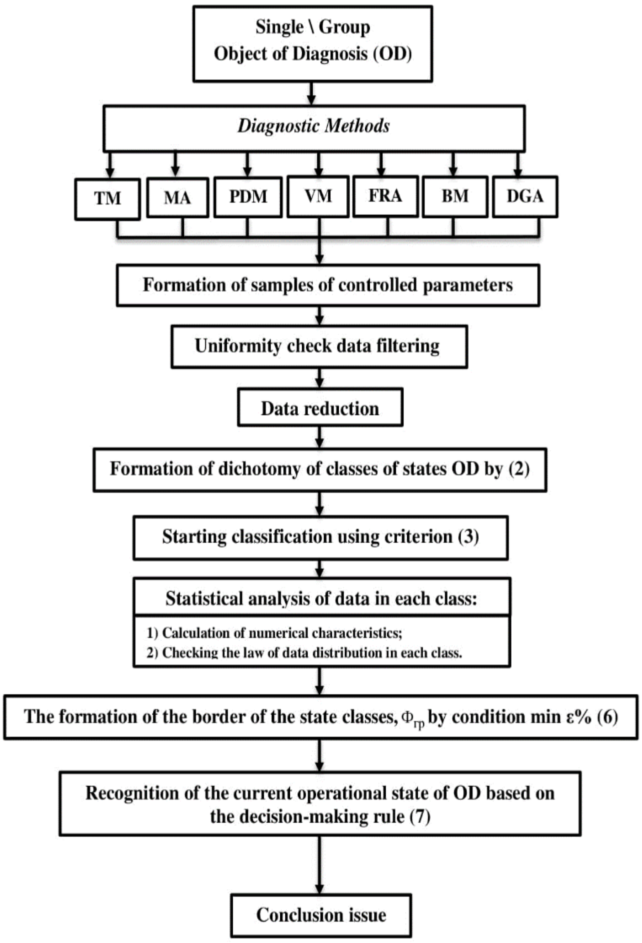


Figure 4. The algorithm of statistical calculations and state estimation of object of diagnosis: dissolved gas analysis (DGA); moisture analysis (MA); partial discharge monitoring (PDM); vibration monitoring (VM)

The total classification error $\varepsilon, \%$ with a decrease in the number of monitored gases n tends to decrease as shown in Figure 3. In part, this is explained by the difference in the sample sizes of RV D in classes S_1, S_2 and with variation n=3, 5, 7 as a result of preliminary division into classes according to the criterion (3) of the initial set of DGA PT protocols. The dependences (8) obtained by approximating the experimental points adequately reflect the adaptive properties of the statistical model of the classifier with variations in the number and composition of the controlled parameters (diagnostic gases) participating in its formation.

$$D_{max};\ 0.9334 \times exp(-0.034 \times n); \varepsilon; 4.1446 \times 1n(n) - 4.3763 \tag{8}$$

At the stage of calculating the RV D according to formula (1), the dependencies (8) can play the role of tuning functions that determine the important characteristics of the reliability of the model from the set of input controlled parameters.

4. CONCLUSION

The relevance of increasing the reliability of diagnostic assessments of electrical equipment, based on which decisions are made to extend its operation or withdraw it for repair, is extremely high since it determines the reliability of the functioning of electrical equipment and the system of electrical power as a whole. The use of the Bayesian classifier as a tool for increasing the methodological reliability of diagnostic assessments, despite some limitations, opens up extraordinary opportunities in the formation of adaptive decision rules that minimize the total recognition error. Models and a method for determining the classifier are proposed. The studies of the influence on the reliability of diagnostic assessments according to the classifier model of the quantity and composition of the controlled parameters involved in its formation have been carried out. Dependencies (8) were obtained, which can be used as functions for setting the reliability characteristics of the classifier model. One of the examples of the practical application of the developed statistical method is considered, its algorithmic implementation is presented, which provides support for computational processes.

REFERENCES

[1] A. S. Khismatullin, “Method for increasing oil resources transformers with longterm operation,” *IOP Conference Series: Materials Science and Engineering*, vol. 327, no. 2, Mar. 2018, Art. no. 22058, doi: 10.1088/1757-899X/327/2/022058.

[2] X. D. Zhang, “Study on feature layer fusion classification model on text/image information,” *Physics Procedia*, vol. 33, pp. 1050–1053, 2012, doi: 10.1016/j.phpro.2012.05.172.

[3] J. I. Aizpurua, S. D. McArthur, B. G. Stewart, B. Lambert, J. G. Cross, and V. M. Catterson, “Adaptive power transformer lifetime predictions through machine learning and uncertainty modeling in nuclear power plants,” *IEEE Transactions on Industrial Electronics*, vol. 66, pp. 4726 - 4737, 2018, doi: 10.1109/TIE.2018.2860532 .

[4] S. Tenbohlen, S. Coenen, M. Djamali, A. Müller, M. H. Samimi, and M. Siegel, “Diagnostic measurements for power transformers,” *Energies*, vol. 9, no. 5, May 2016, Art. no. 347, doi: 10.3390/en9050347.

[5] Z. Moravej and S. Bagheri, “Testing of differential relay operation for power transformers protection using RTDS,” in *30th Power System Conference, PSC 2015*, Nov. 2017, pp. 99–105, doi: 10.1109/IPSC.2015.7827733.

[6] A. Buonanno *et al.*, “Bayesian feature fusion using factor graph in reduced normal form,” *Applied Sciences (Switzerland)*, vol. 11, no. 4, pp. 1–14, Feb. 2021, doi: 10.3390/app11041934.

[7] H. Geranian, S. H. Tabatabaei, and H. Asadi Haroni, “Application of classifiers based on bayes decision theory in gold potential mapping by using geochemical data in sari gunay epithermal gold deposit,” *Journal Of Geochemist*, vol. 1, no. 4, pp. 342–350, 2014.

[8] E. T. Mharakurwa, G. N. Nyakoe, and A. O. Akumu, “Power transformer fault severity estimation based on dissolved gas analysis and energy of fault formation technique,” *Journal of Electrical and Computer Engineering*, vol. 2019, pp. 1–10, Feb. 2019, doi: 10.1155/2019/9674054.

[9] H. De Faria, J. G. S. Costa, and J. L. M. Olivas, “A review of monitoring methods for predictive maintenance of electric power transformers based on dissolved gas analysis,” *Renewable and Sustainable Energy Reviews*, vol. 46, pp. 201–209, Jun. 2015, doi: 10.1016/j.rser.2015.02.052.

[10] A. Lakehal, Z. Ghemari, and S. Saad, “Transformer fault diagnosis using dissolved gas analysis technology and Bayesian networks,” in *2015 4th International Conference on Systems and Control, ICSC 2015*, Apr. 2015, pp. 194–198, doi: 10.1109/ICoSC.2015.7152759.

[11] P. Mirowski and Y. Lecun, “Statistical machine learning and dissolved gas analysis: A review,” *IEEE Transactions on Power Delivery*, vol. 27, no. 4, pp. 1791–1799, Oct. 2012, doi: 10.1109/TPWRD.2012.2197868.

[12] V. M. Levin, “A statistical method for the recognition of defects in power transformers during their maintenance as of state,” *Industrial Energy*, no. 8, pp. 37–42, 2014.

[13] R. M. A. Velásquez and J. V. M. Lara, “Principal components analysis and adaptive decision system based on fuzzy logic for power transformer,” *Fuzzy Information and Engineering*, vol. 9, no. 4, pp. 493–514, Dec. 2017, doi: 10.1016/j.fiae.2017.12.005.

[14] C. Ge, H. Cui, S. Huo, W. Guo, H. Ma, and L. Qin, “Improved DGA methods of power transformer fault diagnosis: a review,” 2018, doi: 10.2991/iceep-18.2018.321.

[15] B. Puza, "Bayesian methods for statistical analysis," ANU press, 2015.

[16] W. Hsu, “Bayesian Classification,” in *Encyclopedia of Database Systems*, L. LIU and M. T. ÖZSU, Eds. Boston, MA: Springer US, 2009, pp. 210–214.

[17] J. I. Aizpurua *et al.*, "Power transformer dissolved gas analysis through Bayesian networks and hypothesis testing," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 25, no. 2, pp. 494–506, Apr. 2018, doi: 10.1109/TDEI.2018.006766.
[18] N. Amruthnath and T. Gupta, "Factor analysis in fault diagnostics using random forest," *Industrial Engineering and Management*, vol. 8, no. 1, 2019, doi: 10.4172/2169-0316.1000278.
[19] *RD 153-34.0-46.302-00: Guidelines for the diagnosis of developing defects in transformer equipment based on the results of the chromatographic analysis of gases dissolved in oil*, Russian Standards and Regulations, Moscow, 2001, Art. no. 41. [Online]. Available: https://runorm.com/catalog/120/767877/
[20] V. M. Levin, "Methodological aspects of assessing state of HPP transformers in monitoring mode," in *2018 XIV International Scientific-Technical Conference on Actual Problems of Electronics Instrument Engineering (APEIE)*, Oct. 2018, pp. 238–243, doi: 10.1109/APEIE.2018.8545915.
[21] V. Levin and N. Kerimkulov, "Rapid assessment of the operational status of the oil-filled transformers," in *2016 11th International Forum on Strategic Technology (IFOST)*, Jun. 2016, pp. 208–212, doi: 10.1109/IFOST.2016.7884229.
[22] V. M. Levin and A. A. Yahya, "Support for decision-making to ensure reliable operation of transformers as part of a responsible power facility," Oct. 2020, doi: 10.1109/FarEastCon50210.2020.9271626.
[23] A. Tumanov, A. Sabanaev, A. Solovyov, and V. Tumanov, "Statistical testing of hypotheses about the form of the factor law of influence by the Kolmogorov criterion," *Journal of Physics: Conference Series*, vol. 1614, no. 1, Aug. 2020, Art. no. 12082, doi: 10.1088/1742-6596/1614/1/012082.
[24] S. Wallot and G. Leonardi, "Deriving inferential statistics from recurrence plots: A recurrence-based test of differences between sample distributions and its comparison to the two-sample Kolmogorov-Smirnov test," *Chaos*, vol. 28, no. 8, Aug. 2018, Art. no. 85712, doi: 10.1063/1.5024915.
[25] W. Feller, "On the Kolmogorov–Smirnov limit theorems for empirical distributions," in *Selected Papers I*, Springer International Publishing, pp. 735–749, 2015.
[26] S. Permana, S. Sumarto, and W. S. Saputra, "Analysis of transformer conditions using triangle duval method," *IOP Conference Series: Materials Science and Engineering*, vol. 384, no. 1, Jul. 2018, p. 12065, doi: 10.1088/1757-899X/384/1/012065.
[27] T. U. Mawelela, A. F. Nnachi, A. O. Akumu, and B. T. Abe, "Fault diagnosis of power transformers using duval triangle," Aug. 2020, doi: 10.1109/PowerAfrica49420.2020.9219802.
[28] T. Mendes Barbosa, J. Goncalves Ferreira, M. Antonio Ferreira Finocchio, and W. Endo, "Development of an application based on the duval triangle method," *IEEE Latin America Transactions*, vol. 15, no. 8, pp. 1439–1446, 2017, doi: 10.1109/TLA.2017.7994790.

BIOGRAPHIES OF AUTHORS

Vladimir Mikhailovich Levin was born in Omsk, Russian Federation in the 1954 year. He received a degree in power engineering from the Novosibirsk Electrotechnical Institute in 1976. In 1983 he received a degree of candidate of technical sciences in the field of electrical power stations and electric power systems. The degree of Doctor of Technical Sciences in the same scientific specialty he received in 2017. Presently he works as the head of the Department of Automated Electric Power Systems at the Novosibirsk State Technical University, Novosibirsk. His scientific interests are in the field of diagnostics and reliability of electric power systems, developing methods and mathematical models for adaptive management of the technical state of electrical equipment of power plants and electrical networks, asset management. He can be contacted at email: levin@corp.nstu.ru.

Ammar Abdulazeez Yahya was born in Baghdad, Iraq, in 1985. He received the BSc degree from the University of Technology, Baghdad, Iraq, in 2007, the M.Sc. degree from Platov South-Russian State Polytechnic University, Rostov on Don, Russia in 2015, and now he is studying Ph.D. 4 year at Novosibirsk State Technical University. He works as a teacher at the University of Technology in Baghdad, Iraq. His scientific interests are in the field of diagnostics, monitoring, and reliability of electric power systems. He can be contacted at email: ammarazez384@gmail.com.