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Adaptive management of technical condition of power transformers

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ABSTRACT

Ensuring reliable operation of power transformers as part of electric power facilities is assigned to the maintenance and repair system, whose important components are diagnostics and monitoring of the technical condition. Monitoring allows you to answer the question of whether the transformer abnormalities and how to do they manifest, while diagnostics allow determining the nature, the severity of the problem, determine the cause and possible consequences. The article presents the results of the author's research on creating an algorithm for adaptive control of the technical condition of power transformers using diagnostic and monitoring data. The developed algorithm implements the decision-making procedure for ensuring the reliable operation of oil-filled transformer equipment as part of the substations of electric power facilities. The decision-making procedure is based on the method of statistical Bayesian identification the states of a transformer based on the results of dissolved gas analysis (DGA) in oil. The method is characterized by high reliability of recognizing defects in the transformer and the ability to adapt the probabilities of the obtained solutions to the newly received diagnostic information. These results illustrate the effectiveness of the developed approach and the possibility of its application in the operation of oil-filled transformer equipment.

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1. INTRODUCTION

The issues of energy-saving and efficient use of limited resources in the electric power industry are quite urgent and relevant. Also, they are inextricably linked with the issues of ensuring the functional reliability of power facilities and the operational reliability of equipment [1-7]. This leads to the identification of an effective strategy for managing the production assets of energy enterprises, in developing algorithms for assessing the technical condition of equipment, making decisions on the type and magnitude of operational impacts, etc. Most well-known scientific studies offer a tactical (situational) approach to solving these problems, which generally gives positive results [8, 9]. However, the obvious preference is for a unified, scientifically based solution for assessing the technical condition of electrical equipment, making decisions on its trouble-free operation and their algorithmic and software [10-13]. One of the promising areas that claim to receive scientifically based practical solutions [14, 15], is based on the application of the methods of the theory of statistical classification and pattern recognition.

Of all the types of equipment of power plants and electric networks, transformer equipment is the most complex, responsible and expensive. Failures of power transformer (PT) are relatively rare, but they lead to serious consequences: violations of technological processes, undersupply of electricity, increased losses. In this regard, the diagnosis and monitoring of PT play an important role in ensuring the operation of current information on the current state. One of the most informative methods for the early detection of oil-filled PT defects is a chromatographic analysis of gases dissolved in oil [16-21]. Dissolved gas analysis (DGA) allows, without turning off the PT, to detect up to 70% of defects in elements of the active part, such as electrical discharges and overheating of various degrees of intensity.

The DGA technique operates with measured concentrations (Ai, i = 1,..,7) of gases dissolved in oil: H2, CH4, C2H4, C2H2, C2H6, CO2, CO, as well as with established limit values (Amaxi) [22-25]. By the methodology [26], the state is assessed according to the following criteria:
- The criterion of boundary concentrations allows to reveal the signs of a developing defect;
- The criterion of relations of pairs of concentrations of characteristic gases allows us to determine the type of the defect;
- The criterion of the relative rate of change of concentration allows us to estimate the degree of development of the defect and its danger for the continued operation of PT.

Despite these advantages, DGA has a significant drawback-the relatively low reliability of the estimates obtained.

2. IDENTIFYING THE TECHNICAL STATE OF PT BY DGA

To increase the reliability of assessing the state of PT by DGA, it is recommended to use a generalized state identifier (GSI), which is calculated using convolution:

$$G = \sum_{i=1}^{7} \left(\frac{A_i}{A_{\max i}}\right)^2 \Big/ \sum_{i=1}^{7} \frac{A_i}{A_{\max i}} \tag{1}$$

The use of GSI [27] guarantees the following set of advantages, very significant from the point of view of the classification task:
- Compactness of the description and generalized assessment of the vector of measured concentrations of diagnostic gases;
- Increasing the sensitivity of the trait to changes in the composition and concentrations of gases caused by the occurrence of a defect in the PT;
- Simplicity of forming class dichotomies and simplifying the conditions for their linear separability.

Consideration (1) as a discrete random variable determines the possibility of generating statistical samples (SS) based on the protocols of multi-year DGA of the considered single PT or a group of the same type transformers operating under comparable conditions. An important property of statistical samples is their sufficient representativeness. The samples combine DGA protocols, according to which, according to the criteria of [26], a developing defect is predicted, or its absence. Thus, initial conditions are formed for splitting the set of possible states of the PT into two mutually opposite classes P1 - “norm” and P2- “deviations from the norm”.The appearance of class dichotomies in the form of two generally intersecting intervals on the positive semi-axis G ∈ [0 - ∞) leads to the formulation of two fundamental questions:
1. Where should I draw the boundary between the classes of states of the PT and how to get it?
2. How much is it advisable to introduce PT state classes for their subsequent reliable identification?

Studies [27, 28] have established that the Bayesian classifier (2) is best suited for describing the boundary between the classes:

$$G_{\max}^{1} = \frac{M_1\sigma_2^2 - M_2\sigma_1^2 + \sqrt{D}}{\sigma_2^2 - \sigma_1^2} \tag{2}$$

or its simplified model (3)

$$G_{\max}^{1} = M_1 + k\sigma_1 \tag{3}$$

Here: M1, M2, σ_2^1, σ_2^2 mathematical expectations and standard deviations SS G in classes P1 and P2 respectively, D – function of listed parameters, k - empirically computational constant from 2 - 3 range. A prerequisite for the correct application of (2) and (3) is single-mode and two-parameter distribution of SS distributions in both classes of states, which in most practical cases is fulfilled.The definition $G_{\max}^{1}$ of (3) allows you to adjust its value based on the minimum total error of diagnosis, $\min(\varepsilon_1 + \varepsilon_2)$, where ε_1 and ε_2 “false alarm” and “defect omission”, respectively. Figure 1 shows the histograms of relative frequencies SS G for classes P1 and P2, compiled from samples of protocols DGA block PT type TDN-250000/220 for 20 years of operation from 1994 to 2013. The figure clearly shows the intersection of the histograms of both classes, which represents the total error of diagnosis. As is well known, an increase in the number of classes of states leads to a decrease in confidence in their identification.

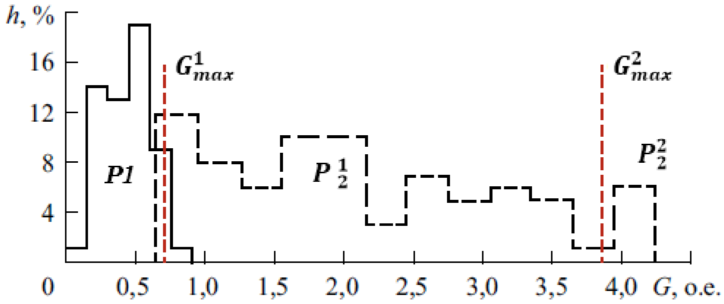

Figure 1. Histograms of relative frequencies G

In [29], it was convincingly shown that the most appropriate option is the dichotomy of classes (P1 and P2). At the same time, the class P2 consists of two subsets P^1_2- “minor deviations” and P^2_2 - “significant (critical) deviations”, between which there is also an interface. According to [29], the boundary between these subsets can be adequately described by the expression $G^1_{max} = M_1 + k\sigma_1$subject to the representativeness of the sample in the class P2. The possibility of obtaining the boundaries of the division of classes on the positive half-line of the sign G makes it possible to form the following criteria and rules for identifying PT states:

- if, $G \leq G^1_{max}$ then "normal";
- if, $G^1_{max} \leq G < G^2_{max}$ then "minor deviations";
- if, $G > G^2_{max}$ then “Significant (critical) deviations”.

The formed decision rules establish a one-to-one correspondence between the quantitative measure of the generalized trait and the characteristics of the operational state PT. The load of the PT is an important operational factor that influences the temperature regime of its operation and, as a result, the results of the technical condition assessment using the DGA method. A significant increase in the PT current load (I_{load}) even in a transformer in the “normal” state causes an increased heat generation and an increase in the concentrations of hydrocarbon gases typical for overheating: CH4, C2H4, C2H6, which increases the probability of an erroneous diagnosis. In order to increase the reliability of identifying the state of "deviation from the normal," it is advisable to establish a correlation dependence G^1_{max} (K_{load}), given the stochastic properties of these variables. A necessary condition for achieving this goal is the formation of two time-synchronized statistical samples of the SS G and $K_{load} = I_{load} \backslash I_{l.nominal}$ in class P1.

Here $I_{l.nominal}$ is the nominal current of the low voltage winding PT.Determination of the correlation functions $M1(K_{load})$,$\sigma 1(K_{load})$, the calculation of the desired dependence G^1_{max} (K_{load}) by the expression (3), the approximation of the obtained set of calculation points by the analytical expression:

$$G^1_{max} = \alpha \exp [\beta K_{load}], \quad (4)$$

where α,β are constants of approximation, represent the sequence of solving the set task.As a result of the use of (4), an adaptive identification of the state of the PT is provided, depending on its current load current, at which the concentrations of diagnostic gases are measured by DGA and the G value is calculated.

3. PRACTICAL IMPLEMENTATION OF THEORETICAL POSITIONS

3.1. Monitoring the state of PT on the dynamics of change the generalized trait

Consider the practical implementation of adaptive control of the technical condition of PT on the example of the operating history of the block transformer TDN-25000/220 in NTPS-5 (Novosibirsk Thermal Power Station-5). The retrospective of the DGA protocols for 20 years of operation showed an excess of the boundary concentrations of such diagnostic gases as C_2H_2, C_2H_4, CH_4, C_2H_6, in the interval 06.2006-02.2013, which indicates a stable thermal defect, presumably associated with a violation of the circulation of magnetic fluxes in the steel core. The indicated interval of operation of a PT with a developing defect can be clearly observed by the change in the dynamics of the generalized attribute G(t) shown in Figure 2. The results of the monitoring inform that the investigated PT is in a state of "deviation from the normal" (G^1_{max} <G < G^2_{max}).In certain periods of time,the state of ST deteriorates and goes into the category of "critical deviation" (G> G^2_{max}). Continued operation of the PT in this state is associated with an increased risk of failure and requires the timely introduction of adequate operational impacts.

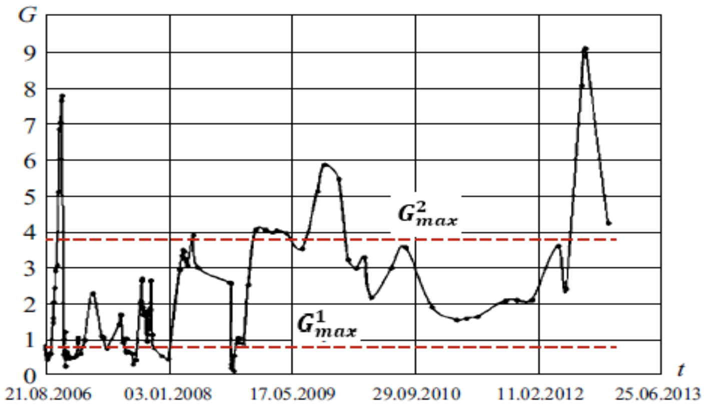

Figure 2. Monitoring the status of PT by G(t)

3.2. Increased identification accuracy

In the proposed statistical models, the adaptation of the reliable identification of the states of the PT is possible, first, by choosing the value of the computational constant k = 2–3 by the criterion min (μ_1+ μ_2). As already mentioned, the total diagnosis error is visually the area separated by the boundary function G^1_{max} from the frequency histograms in each of the classes of states P1 and P2 as shown in Figure 1. Table 1 shows the selection results K, according to which the minimum total identification error (ε_1+ε_2) =1.159% is provided with K=2.2 and G^1_{max}=0.765**.**

Secondly, an adaptation of reliable identification of PT states can be realized using (4). Figure 3 shows the approximation of the boundary function G^1_{max} for the studied PT with coefficients α=0.4242, β=0.7716. This allows for the operational adaptation of decision rules on the current value K_{load} PT.

Table 1. Selection results constants K

№	k	G^1_{max}	ε_1, %	ε_2, %
1	2	0,735	3,05	1,159
2	2,2	0,765	0	1,159
3	2,4	0,796	0	1,159
4	2,6	0,827	0	1,494

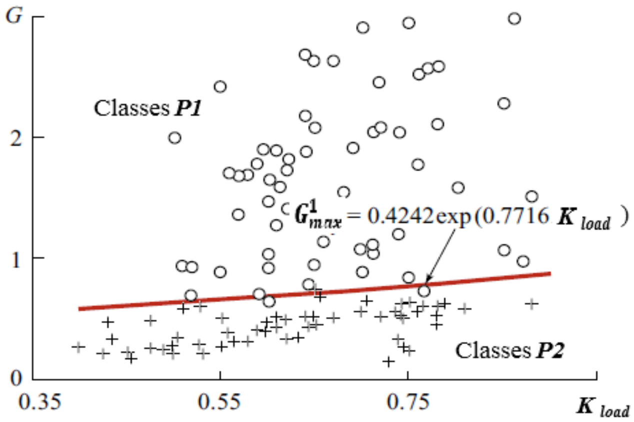

Figure 3. Approximation of the boundary function in the state space PT

3.3. The intensity of the dynamics of changes in the generalized sign

Assessment of the intensity of the dynamics of changes in the generalized characteristic G is appropriate in the case when the presence of a developing defect is predicted and the state of the PT is characterized as “deviation from the normal”. In this case, there is a need to determine the degree of danger of a defect for the further operation of PT. It is obvious that the results of such an assessment may affect the results of decision-making and should be reflected in the criterion relationships. by the method DGA [26], an assessment of the degree of danger of a defect developing in PT is made according to the relative rate of change of concentrations of diagnostic gases dissolved in oil $V_{rel\ i}$. To establish a quantitative measure of the danger of a developing defect, two maximum permissible values of the maximum relative rate of increase in the concentrations of characteristic gases are introduced 10% and 15% per month. If max $V_{rel\ i} \geq 10\%$ per month and <15% per month, it is recommended to put the PT on the increased control by DGA, and if max $V_{rel\ i}$ >15% per month, then it is required to remove the PT from work with the subsequent planning of repair.

4. ALGORITHM OF ADAPTIVE STATE CONTROL PT

The decision-making algorithm is an ordered sequence of actions aimed at achieving the set goal. In this case, the goal is to develop reasonable and timely recommendations on the direction and importance of operational impacts on the PT by the assessment of its current technical condition, determined using the developed models and decision rules. The algorithm of adaptive control of the technical state of the PT as shown in Figure 4 includes the following computational and logical blocks:

- collection and processing of data, the formation of diagnostic statistics;
- calculation of boundary functions and correlation dependencies;
- calculation of the current value of the generalized characteristic, taking into account the actual load on the transformer;
- criterion assessment and identification of the current operational status of the transformer;
- Decision making on the nature of operational impacts on the PT.

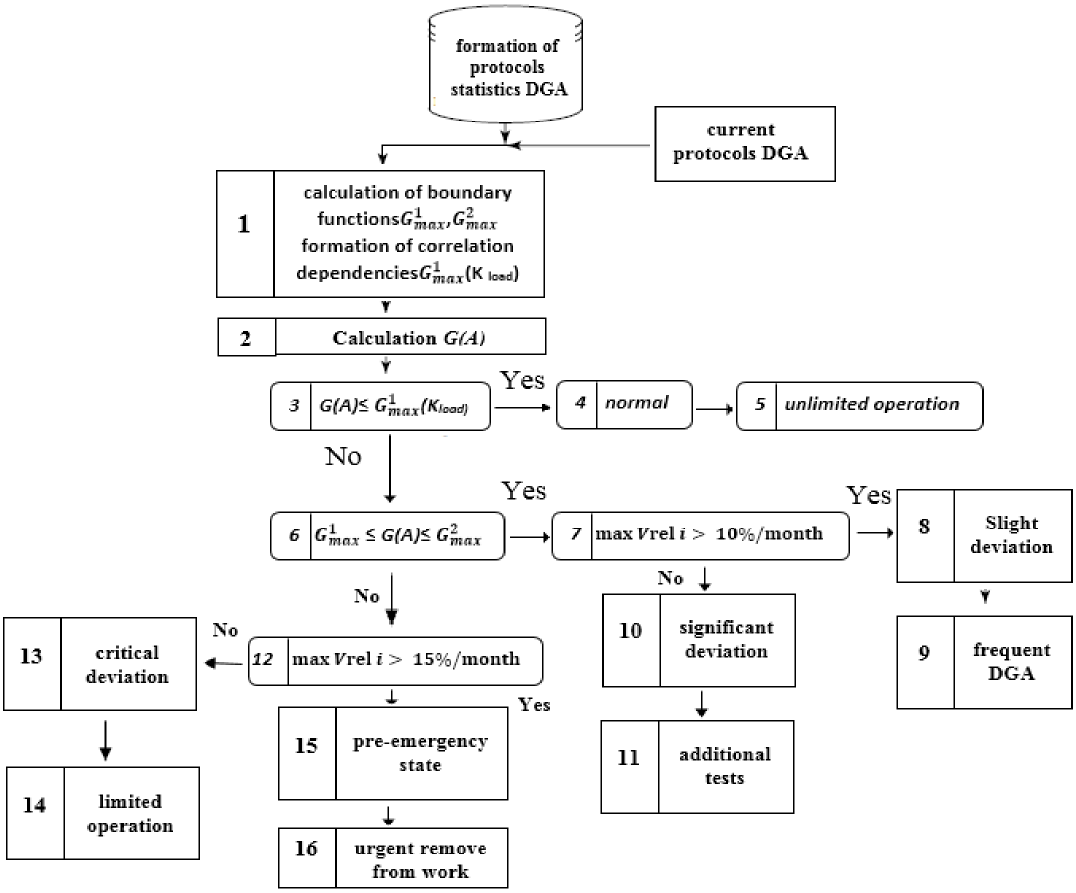

Figure 4. Algorithm for adaptive control of the technical state of a power transformer

Adaptability of the developed algorithm gives, firstly, the ability to customize the boundary function G_max^1 by the condition of minimum total identification error, secondly, the ability to take into account the dependence of the boundary function on the actual current load PT G_max^1 (Kload) , recorded during the formation of the protocol for the analysis of dissolved gases DGA. This allows with a high probability to provide reliable identification of the current technical condition of the PT, and therefore, the validity of the recommended operational impacts concerning it. The launch of the algorithm is performed at the time of receipt of the protocol of the current DGA PT. Re-computation of boundary functions and correlation dependencies occurs as the statistical material is updated (DGA protocols), but at least once a year. This is due to the intensity of updating statistical samples, which depends on the level of the hierarchy of software and computing resources. In the case of a centralized level of hierarchy (the server of the network enterprise), statistical samples form the DGA protocols of the same type of transformers used in similar operating conditions. This ensures that the samples are sufficiently representative at the annual operating interval. In the case of the local hierarchy level, the sampling is carried out in the mode of diagnostic monitoring, which is also acceptable from their representativeness.

5. CONCLUSIONS

Situational decisions related to the use of expert assessments of the degree of workability of individual units and groups of equipment of the same type give positive results, but cannot be opposed to a unified, scientifically-based approach to assessing the current state of electrical equipment, making decisions on its trouble-free operation, and their algorithmic and software. The proposed statistical models, decision rules and an algorithm for adaptive control of the technical condition of a power transformer provide an effective solution to the specified problems. The results of their use in the practice of operating a power transformer are confirmed by concrete examples and demonstrate a high level of reliability of diagnostic evaluations and the validity of the recommended operational effects.

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