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THE METHOD OF FAILURE PREDICTION IN THE HIGH VOLTAGE TRANSFORMER EQUIPMENT BASED ON THE METRIC CLASSIFICATION OF DIAGNOSTIC FEATURES' TRENDS

The process of diagnosing of high-voltage transformers has been analized. The problem of measurements clustering of transformers' diagnostic features has been solved. The method which is based on the metric classification and allows predicting the residual life of the high-voltage transformer equipment has been proposed. An experimental study of the proposed method which confirmed its effectiveness in practice has been performed.
Classification, diagnostics, metric, prediction, transformer.

Introduction

Early identification of trends for faults in the high-voltage equipment helps to prevent progressing of defects; to carry out repair right in time; to reduce maintenance costs. Unlike the diagnosis "in fact", forecasting lets eventually predict the faults occurrence, even if there were appeared no significant deviations of controlled parameters from their certified values.

As the rule, the faults progress goes gradually and continuously at standard modes and it is getting faster in case of the emergency mode [1]. The current transformer residual life prediction methods are known, e.g. [2]. Those methods do not provide early faults detection and they cannot be used to predict the residual life for a long period of time. Thereby the effectiveness of the faults progress preventing measures is reduced. Therefore, it is actual and important to predict equipment failure according to diagnosis data at the earliest stages until the fault is not turned into its critical state.

The failures prediction in the high voltage transformer equipment is based on the mathematical model for the metric data classification [3-6], that allows producing the learning systems. It enables to increase the effectiveness of diagnosing the high-voltage equipment. This

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paper proposes a method which is based on the calculations. It lets predict the failures in the high voltage transformer equipment basing on the fact of a given number of diagnostic features.

1. Problem definition of forecasting faults in high voltage transformer equipment

For diagnosing the database with the results of measurements will be used. Measurements are provided for some analogue groups of equipment. The state of this equipment is known according to the scale "functional - refusal" at the time of measurement. Let the database has a plethora of those sets (1):

$$D = \langle n, t, x, y \rangle, \tag{1}$$

where n is object\`s number, $n = \overline{1, N}$; $t$ is relative discrete measurement time, $t = \overline{0, T_d}$; $x$ is measurement vector of results sizing $I$; $y$ is object\`s state, $y = 0$ is “refuse”, $y = 1$ is “serviceable”; N is database objects number. To convert discrete time to the analogue time the following formula is used: $t_н = t_{но} + t\Delta$, where $t_{но}$ – the time when the 1st measurement occurs for this object; Δ is range of time between two measurements.

Then basing on the given multitude D (1) the model $M = M(D)$ should be constructed. It lets execute diagnosis (to specify the output value y) of the HV equipment state according to the set of its characteristics. For the equipment that is accepted as serviceable the model lets specify the residual life service.

The task of the paper is to work out the method of faults forecasting for HV transformer equipment, that allows forecasting at the earlier stages of faults progressing.

2. Method of faults prediction in the high voltage transformer equipment on the basis of metric classification

To specify the transformer state T_q basing on the metric classification [3] the model should be built $M = M(D)$. It is a set of geometric center points for the classes. In the D base there are specified the objects, that are accepted as refusal. Then their parameters should be united in the moment T_d to the k_0 class. Objects measurements are united to the k_1 classes, that are accepted as serviceable for $t \in [0, T_d]$. Parameters for objects that were taken at the previous time should be united to the $k_{\Delta t}$, $k_{2\Delta t}$, $k_{3\Delta t}$ classes etc. These measurements were taken at the moment of time $T_d - 1$ for the $k_{\Delta t}$ class, $T_d - 2$ for the $k_{2\Delta t}$ class. Meaning of *i*-th coordinate ($i = \overline{1, I}$), that is the center of *k*-th class C_i^k ($k = 1, 2, ..., K$) should be specified according to the formula (2):

$$C_i^k = \frac{1}{N_k} \sum_{j=1}^{N_k} \{x_{ij}\}, \tag{2}$$

N_k is the number of measurement in the set *D* (1) that is related to the k class; x_{ij} is the meaning of *i*-th parameter for *j*-th sample of the object related to the k class.

Having calculated the coordinates of classes centers set $C^1, C^2, ..., C^K$, $C^k = \{C_1^k, C_2^k, ..., C_{N_x}^k\}$ the relation of the samples T_q to some classes $\{1, 2, ..., K\}$ can be specified for any sample that is out of the *D* (1) set, basing on the input meanings $\{x_{1q}, x_{2q}, ..., x_{N_x q}\}$ in their nearness to centers $C^1, C^2, ..., C^K$.

Different metrics could be used [5, 6]:

– Euclidean metric:

$$R(T_q, C^k) = \sqrt{\sum_{i=1}^{N_x} (x_{iq} - C_i^k)^2}; \tag{3}$$

– Hamming metric:

$$R(T_q, C^k) = \sum_{i=1}^{N_x} \left| x_{iq} - C_i^k \right|; \tag{4}$$

– Maximum value of the distances of every coordinate:

$$R(T_q, C^k) = \max_{i=1,2,...,N_x} \left| x_{iq} - C_i^k \right|; \tag{5}$$

– Minimum value of the distances of every coordinate:

$$R(T_q, C^k) = \min_{i=1,2,...,N_x} \left| x_{iq} - C_i^k \right|. \tag{6}$$

Depending on the distance $R(T_q, C^k)$ then the relating of transformer occurs to the *k class*, that is situated at the least distance $R(T_q, C^k)$:

$$k(T_q) = \arg\min_{k=1,2,...,K} R(T_q, C^k), \tag{7}$$

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where $\underset{k=1,2,...,K}{\arg\min}$ is the function, that specifies the number of the k class according to the minimal distance $R\left(T_q, C^k\right)$.

There could be situations when the results for a transformer will be situated at the same distance to different classes (e.g., $k_{a\Delta t}$ & $k_{b\Delta t}$). In this case the following measures should be taken:

– in order to reduce the potential losses because of the wrong decision (to accept the sample as serviceable set in the case when it should be accepted as refusal) the transformer T_q should be relates to the $k_{a\Delta t}$ class with geometric center C^k, that is closer to the k_0 class ($R\left(C^{k_0}, C^{k_{a\Delta t}}\right) < R\left(C^{k_0}, C^{k_{b\Delta t}}\right)$);

– to specify the sample T_q as a part of $k_{a\Delta t}$ class, that contains more numbers of samples in the set D ($N_{D|k=a\Delta t} > N_{D|k=b\Delta t}$).

As the result of making the choice whether the equipment should belong to k_0 class (refusal) or k_1 class (serviceable). At the making decision $k = k_{a\Delta t}$ transformer is considered as the one, that his time to the fault is not less $a\Delta t$, where a is a value that is equal to the intervals number Δt before transformer fault. If the value $a\Delta t$ is less than minimum acceptable time of waiting $t_{\min}$ ($a\Delta t < t_{\min}$), the measures of transformer diagnosis should be provided [7–9].

There is depicted the graphical interpretation of the lot of samples, that corresponds to different $k_0, k_{\Delta t}, k_{2\Delta t}, ..., k_{a\Delta t}, k_1$ classes in the 2D space of normalized x_1, x_2 curves in the fig 1. There are shown classes, where $y = 0$, i.e. the fault equipment is fixed and $y = 1$ equipment is processed as serviceable with the different grade of serviceability.

On the fig.1 there is shown possible case for gradual transfer from serviceable state ($y = 1$; $k = k_1$, $k = k_{2\Delta t}$, $k = k_{\Delta t}$) to the fault state($y = 0$; $k = k_0$).

Thus, the proposed method of predicting failure in the high voltage transformer equipment on the basis of metric classification involves the creation of a diagnostic model by splitting the original set (equipment parameters) on classes depending on the time before the fault event, as well as the calculation of the geometric center of each class.

Calculating the coordinates distance for measured parameters of diagnosed transformer to the centers of model classes it is possible to determine the closest class and therefore, the residual life of the transformer.

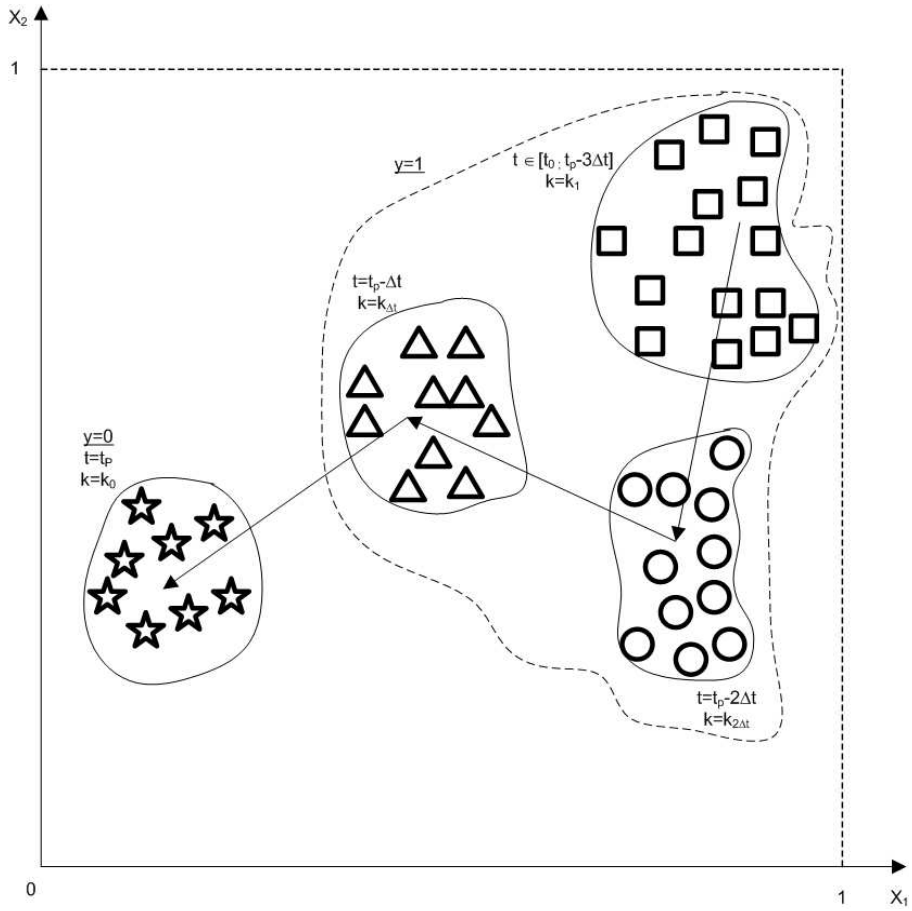

Figure 1 – Graphical interpretation of deviating x_1, x_2 curves meanings at the gradual transfer of samples (transformers) from serviceable state ($y = 1$) to the fault state ($y = 0$)

3. Experiments and results

For the experiments the proposed method of predicting failure in the high voltage transformer equipment on the basis of metric classification program was implemented with the measuring current transformers. On the basis of this method and software, the task of state diagnosing of paper-oil insulation for measuring current transformers ТФКН-330 was solved. The transformers were in service of ПАО "ДТЭК Днепроэнерго".

As the input parameters there were chosen the next parameters in order to construct the diagnosis model $M = M(D)$ [10]:

– dielectric loss tangent of basic insulation at the operating voltage, x_1;

– basic insulation capacitance deviation from the rated value, x_2;

– the temperature of the ambient air, x_3.

The part of the measurements results set D (1) is listed in the table 1, where Y =1 is serviceable transformer state, Y =0 is fault ("refusal") state.

Table 1

The part of the transformer measurements results set using for the diagnosis model $M = M(D)$

Measurement number	Transformer number	Parameters values			Y	k class
		x_1	x_2	x_3		
1	1	0,460	0,937	0,563	1	$k_{3\Delta t}$
10	3	0,440	0,644	0,781	1	$k_{3\Delta t}$
15	1	0,767	0,286	0,500	0	k_0
18	4	0,574	0,928	0,332	0	k_0
34	6	0,499	0,880	0,767	1	$k_{\Delta t}$
45	8	0,490	0,933	0,900	1	$k_{\Delta t}$
47	8	0,468	0,882	0,333	1	$k_{2\Delta t}$
6	1	0,478	0,955	0,643	1	$k_{2\Delta t}$
71	11	0,407	0,877	0,964	1	k_1
91	13	0,233	0,962	0,435	1	k_1
...	...	...	...	...	...	...
183	15	0,609	1,0	1,0	0	k_0

The measurements of transformers were taken with the average time of $\Delta t = 3$ months. The task was to build the model $M = M(D)$ that will let specify the trends for faults appearance before $t_{progn} = 9$ months of their appearance and complete operation refusal of transformer. Therefore the set of measurement D (columns x_1, x_2, x_3, Y in the table 1) was divided into the k_0, k_1 classes corresponding to the time before fault event, and into $C = \frac{t_{progn}}{\Delta t} = \frac{9}{3} = 3$ for the class ($k_{\Delta t}, k_{2\Delta t}, k_{3\Delta t}$), corresponding to the states of gradual transfers from serviceable state to the refusal state.

After the classes splitting (transfer $D \to D'$) the next specification of center classes have been specified according to the formula (2). Results of centers splitting are listed in the table 2.

Table 2

Classes' centers

Class k	Classes center coordinates meanings C_i^k		
	x_1	x_2	x_3
k_0	0,5222	0,8551	0,5159
$k_{\Delta t}$	0,4880	0,8505	0,7462
$k_{2\Delta t}$	0,4696	0,8491	0,7257
$k_{3\Delta t}$	0,4595	0,8580	0,6268
k_1	0,4341	0,8661	0,7683

Then every measurement of transformer T_j was corresponded to the $k = k_0, k_{\Delta t}, k_{2\Delta t}, k_{3\Delta t}, k_1$ classes in accordance with input parameters x_1, x_2, x_3 and their nearness $R\left(T_j, C^k\right)$ to the classes centers, using Euclidean metric (3) and the formula (7). Error E of the constructed model $M = M(D)$ was calculated as a relation of wrong classified transformers N_{err} to their common number N_D in the set D that are shown in the table 1:

$$E = \frac{N_{err}}{N_D} = \frac{9}{183} = 0{,}049\,. \tag{8}$$

To check the model adequacy $M = M(D)$ its usage for the D_{test} data was executed. Those data do not belong to the D set. Wherein the number of transformer measurements for D_{test} set was $N_{D_{test}} = 134$ un. Error E_{test} of the model $M = M(D)$ was calculated in the following way, calculated for the D_{test} data.

$$E_{test} = \frac{N_{err,test}}{N_{D_{test}}} = \frac{12}{134} = 0{,}089\,. \tag{9}$$

It is clear that error E_{test} for the given D_{test} is a little bit greater than E, calculated for the data D. Both characteristics meanings E &

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E_{test} are in the range of allowable error of 10%, that allows making decision that it is expedient to use the proposed method in practice. Furthermore all cases of wrong classification have to do with the case of processing serviceable transformers as the faulty ones. That is not so significant than the case of processing the faulty transformer as serviceable one.

Conclusion

In this paper the problem of forecasting the actual failures in high voltage transformer equipment was solved.

Scientific novelty lies in the fact that there was developed a method of predicting failures in high voltage transformer equipment on the basis of metric classification, which involves splitting the original set on classes of the characteristics of transformers depending on the time before their failure, the calculation of the geometric center coordinates for each of the classes in the space of normalized characteristics. Belonging diagnosed transformer to one of these classes was determined by the coordinates of its minimum deviation of the current characteristics of the coordinates of the centers of classes. Transformer belonging to a particular class of the proposed model was characterizes its residual life, with an accuracy that depends on the characteristics of the measurement interval used to construct the model. This allows you to identify faults occurring at the initial stages.

The practical value of these results is that the developed software that implements the proposed method and solved the practical problem of diagnosing the state for paper-oil insulation measuring current transformers.

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