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AUTOMATIC DIAGNOSIS OF POWER TRANSFORMERS BASED ON DISSOLVED GAS ANALYSIS – FIRST LEVEL OF DIAGNOSIS USING VAC AND VSC INFERENCE METHODS

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Abstract − Assessment of power transformer condition is very important for utilities, to ensure continuous power transmission and power supply. Therefore, different techniques are used for condition assessment, as off-line diagnostics and on-line monitoring. The off-line diagnostics has some time period between consecutive diagnoses, and during that period the condition is unknown. Diagnostic tools in monitoring system usually comprise comparison of values of monitored quantities to preset limits, and alarming if these limits are exceeded. In this way weak diagnostic capabilities are achieved.

Therefore, a new diagnosis model for assessment of condition of oil immersed power transformers was developed. This model is aimed to continuously and automatically diagnose transformer condition. The diagnosis principle is interpretation of dissolved gas analysis (DGA) data using several standardized interpretation methods. Then, on the basis of obtained diagnoses an overall diagnosis is inferred using VAC, VEV or VSC inference methods in a similar way as it is done by the human diagnostician.

The diagnostic model shows excellent application flexibility, high robustness and significant diagnostic accuracy.

Keywords: automatic diagnosis, power transformer, inference method

1. INTRODUCTION

Equipment in infrastructure systems is always designed for certain lifetime. An example of such equipment is HV equipment in power system. Traditionally, this equipment is replaced after its projected lifetime has expired. As thirty-forty years ago huge investments in power systems happened around the world, lifetime of this equipment has recently expired, or it will expire soon.

Recent liberalisation of electric power market brings the competition in this, traditionally monopolistic market. Competition forces utilities to decrease costs of production, transmission and distribution of energy, as well as costs of equipment maintenance. It also increases demands on reliability of energy supply, and enforces utilities to carry out further technical and technological development of the power system to assure their competitiveness on the market in the future.

Utilities face the challenge that huge investments are necessary for replacement of aged equipment, but at the same time significant part of the fleet is in good condition, and, under certain circumstances, it is available for further exploitation [1].

The most often used solution is keeping aged equipment in service with application of continuous condition monitoring, as long as the equipment is in good condition [2].

2. APPROACHES TO TRANSFORMER CONDITION ASSESMENT

Systems for continuous condition monitoring of generators, transformers, circuit breakers, power lines etc. are nowadays available on the market [3].

Transformer condition monitoring systems measure values of many quantities, process and archive collected data, but the diagnostic ability of such systems is quite poor, often consisting of comparison of actual values to alarm limits, and alarming when these limits are exceeded.

As such functions are not efficient enough for condition assessment, newer and better diagnosis systems, based on artificial intelligence and multivariate statistics have been developed. The most often systems are based on different types of neural networks (NN), like MLP NN (Multi-Layer Perceptron NN), BP NN (Back-Propagation NN), GR NN (General Regression NN) etc [4], [5], then other techniques like fuzzy logic, expert systems, decision trees, support vector machine, evolutionary programming, evidential reasoning [6] and many other techniques.

All of these techniques have its advantages and disadvantages. Hence several techniques are used to constitute a hybrid diagnosis system [7]. These systems are verified measuring their classification accuracy. The highest accuracy is usually achieved using NNs. There is a reason for concern about general application of such systems. In fact, most of these systems are trained and tested using few tens, or few hundred samples, because it is very difficult to find enough, or better to say many samples of transformer faults. It is especially difficult to find enough samples of each type of fault for all types of transformers. As for training of NN much more examples are necessary, NN classification capabilities for wide spectra of transformer types are questionable. The necessity for application of diagnosis system for wide spectra of transformer types, better training features of system, and necessity of on-line diagnostic applications where reasons for investigation of other approach to transformer diagnosis.

3. TRANSFORMER INSULATION SYSTEM

As this research is related to transformer insulation system, the most important stresses, degradation of this system, and degradation products are shortly described.

Insulation system is a key component of any electric device. Most insulation systems in power transformers consist of mineral transformer oil and cellulose insulation such as paper, pressboard and transformerboard [8]. These materials are organic materials and they are subject to degradation. Therefore, insulation system is the most vulnerable component of transformer.

Cellulose insulation in transformer enables dielectric strength and dielectric distance in windings, and distances of windings from components with different potential. Mineral oil enables cooling of transformer, but also it enables dielectric strength.

Insulation system is exposed to thermal, electric, mechanic stresses and stresses due to environmental influences. Effect of any stress is ageing of insulation.

During normal transformer operation and especially during degradation of insulation system gases are generated. Some of these gases are:

- hydrocarbons and hydrogen: methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2) and hydrogen(H_2)
- carbon oxides: carbon monoxide (CO) and carbon dioxide (CO_2)
- non fault gases: oxygen (O_2) i nitrogen (N_2)

Main faults that cause generation of gases are:

- partial discharges (PD)
- thermal degradation (T)
- arcing (D)

Generated gases are dissolved in transformer oil. Distribution of gases can be related to the fault type, and trend of gas generation can indicate severity of the fault.

4. DGA BASED TRANSFORMER DIAGNOSIS

The DGA method is often used in practice. Good results in power transformer condition assessment can be achieved using this method [8].

It consists of taking the oil sample from the transformer according to standardized and well defined procedure. The oil sample is analyzed, and dissolved gases are identified and quantified, also through known procedures. After gases are quantified, results are interpreted. There are numerous interpretation schemes or methods for the interpretation of DGA results. The IEC methods are:

- IEC 60599-1999 (IEC99) [9],
- IEC 599-1978 (IEC78) [10],
- Duval triangle method (MDT).

The IEEE methods are [11], [12]:

- Doernenburg method (DB),
- Original Rogers ratio method (RG3),
- Refined Rogers ratio method (RG4),
- Key gas method (KG).

There are also other interpretation methods, like logarithmic nomograph (LN) etc.

The main problem in using these methods is that different methods applied to the same sample result in different, and often in contrary diagnostic decisions. DGA results of 8 samples are presented in table 1 (column “Diagnosis”) along with interpretation results of these samples using eight interpretation methods.

Table 1. Examples of interpretation of DGA results using different interpretation methods.

No.	Diagnosis	IEC 78	IEC 99	MDT	RG3	RG4	KG	LN	DB
1	NF	D1	ND	DT	D2	ND	ND	ND	NF
2	PD	PD	T1	T1	PD	PD	PD	DT	NF
3	T1	T1	ND	T2	T1	T3	ND	DT	NF
4	T2	T1	T1	T3	ND	T1	ND	T	T
5	T3	T2	T2	T3	T2	ND	ND	T	T
6	DT	ND	ND	D2	ND	ND	T3	D2	ND
7	D1	D1	D1	D1	ND	D1	ND	D2	NF
8	D2	ND	ND	T2	ND	ND	PD	ND	NF

The meaning of diagnosis from table 1 is explained in table 2.

Table 2. Meaning of diagnosis abbreviations.

No.	Diagnosis	Meaning
1	NF	Normal condition
2	PD	Partial discharges
3	T1	Thermal fault, t<300 °C
4	T2	Thermal fault, 300 °C≤ t<700 °C
5	T3	Thermal fault, t≥700 °C
6	DT	Mixed thermal and discharge fault
7	D1	Discharges of low energy
8	D2	Discharges of high energy

The only way to combat the problem of different decisions for the same sample is usage of diagnostician’s knowledge and experience. Human verification of interpretation results is completely individual process, so it couldn’t be unified, or defined in procedure form. Because of all, the interpretation of the DGA results is described in literature as “art, but not science”. Nevertheless, combining interpretation method results and human knowledge and experience, brings good results in transformer condition assessment.

5. AUTOMATIC DIAGNOSIS SYSTEM

On the bases of shown samples in table 1, it is obvious that automatic diagnosis of transformer condition, based on DGA results and interpretation schemes is very complex problem. It is multidisciplinary problem, the dependence of the fault and appurtenant gas concentrations is markedly nonlinear, and finally, the human interpretation skills must be simulated.

In spite of this, the problem of automatic diagnosis is solved developing an inference model. This model makes decision using newly developed inference methods. These methods use specifically defined parameters, resulted from multivariate analysis of classification results of interpretation methods.

All interpretation methods, except KG and LN, are implemented in standard form. KG is implemented using fuzzy logic, and LN is implemented using the same inference model used at the level of automatic diagnosis system (ADS). The inference model settings and number of inputs (votes) are different at LN level than that at the level of ADS.

A flowchart of the automatic diagnosis procedure is shown in Fig. 1.

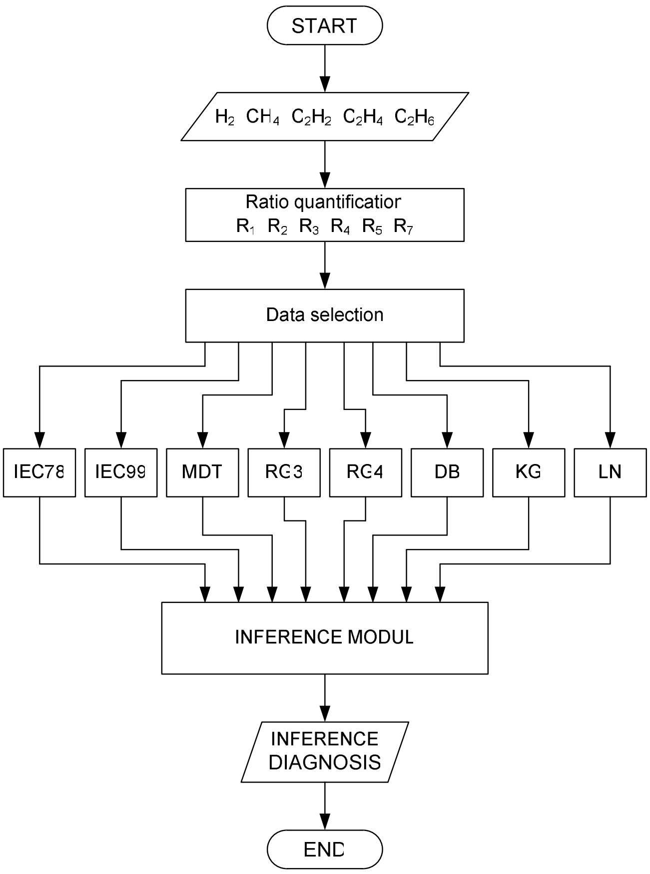

Fig. 1. Flowchart of automatic diagnosis procedure.

In ADS at first concentrations of hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_4) and ethane (C_2H_6) are measured using on-line DGA system. Then ratios of gas concentrations R_1 to R_7, used in interpretation methods, are quantified and distributed to appropriate methods. Each method assesses diagnosis on the basis of these ratios. All assessed diagnoses are then forwarded to inference model, witch inferences the overall diagnosis on the basis of mathematical model.

The same principle of diagnostics is implemented at the level of LN interpretation method.

6. MATHEMATICAL MODEL OF AUTOMATIC INFERENCE

6.1. Coordination of diagnosis

Automatic inference is performed on the basis of diagnostic results of interpretation methods. As interpretation methods assess diagnoses in different ways, their diagnoses are coordinated according to table 3, to be able to use them in the same voting process, and to be able to assess the overall diagnosis. Diagnoses are not completely coordinated, and this level of coordination is the third level of diagnosis.

Table 3. Coordination of diagnoses (third level).

Diag-nosis	IEC78	IEC99	MDT	RG3	RG4	DB	KG	LN	ADS
NF	NF	NF	NF	NF	NF	NF	NF	NF	NF
PD	PD	PD	PD	PD	PD	PD	PD	PD	PD
T1	T1	T1	T1	T1	T1	T	-	T	T
T2	T2	T2	T2	T2	-		-		
T3	T3	T3	T3	T3	T3		T3		
DT	-	-	DT	-	-	-	-	DT	
D1	D1	D1	D1	-	D1	-	D	-	D
D2	D2	D2	D2	D2	D2	D2		D2	

As methods have different format of output diagnoses at the third level, two additional steps of coordination are applied. This resulted in completely coordinated diagnose (first level of diagnosis), which are presented in table 4. Levels of diagnosis serve as resolution tuner of this diagnosis model.

Table 4. Coordination of diagnoses (first level).

Diag-nosis	IEC78	IEC99	MDT	RG3	RG4	DB	KG	LN	ADS
NF	NF	NF	NF	NF	NF	NF	NF	NF	NF
PD	PD	PD	PD	PD	PD	PD	PD	PD	PD
T	T	T	T	T	T	T	T	T	T
D	D	D	D	D	D	D	D	D	D

Interpretation methods are considered as voters, and their diagnoses are considered as candidates for inference diagnosis.

In this research few methods are developed [13]. VAC and VSC inference methods are described and compared here.

6.2. VAC inference method

VAC inference method, or method of **V**aluation of **A**ll **C**andidates, assigns matrix of weighting factors P_j to each voter. Weighting factors are estimated during training, and they are used later during voting and inference.

$$P_j = \begin{bmatrix} p_{11}\ p_{12} \cdots p_{1j} \cdots p_{1n_c} \\ p_{21}\ p_{22} \cdots p_{2j} \cdots p_{2n_c} \\ \vdots \\ p_{i1}\ p_{i2} \cdots p_{ij} \cdots p_{in_c} \\ \vdots \\ p_{n_c 1}\ p_{n_c 2} \cdots p_{n_c j} \cdots p_{n_c n_c} \end{bmatrix}, \tag{1}$$

where p_{ij} is weighting factor, and n_c is the number of candidates.

Voting result of the j^{th} voter is voting vector G_{Pj}:

$$G_{Pj} = \begin{bmatrix} g_{P0j} \\ g_{P1j} \\ \vdots \\ g_{Pij} \\ \vdots \\ g_{Pn_c j} \end{bmatrix}, \tag{2}$$

where g_{Pij} is the value of j^{th} voter support for i^{th} candidate.
$g_{Pij} = 0$ if j^{th} voter doesn't vote for i^{th} candidate,
$g_{Pij} = 1$ if j^{th} voter does vote for i^{th} candidate.

Pondered voting vector of j^{th} voter F_j is defined as:

$$F_j = \left(G_{Pj}{}^{T} \cdot \left(\left(G_{Pj}{}^{T} \cdot P_j \right)^{T} \right) \right) \cdot G_{Pj} \tag{3}$$

Counting of votes and assessment of support to individual candidates is defined according to (4):

$$P_D = \frac{1}{\sum_{i=1}^{n_c} p_i} \cdot \sum_{j=1}^{n_c} F_j, \tag{4}$$

where P_D is the vector of support to individual candidates, and:

$$P_D = \begin{bmatrix} p_0 \\ p_1 \\ \vdots \\ p_i \\ \vdots \\ p_{n_c} \end{bmatrix}, \tag{5}$$

where p_i is a magnitude of total support of all voters to i^{th} candidate.

Candidate with highest support p_i is announced as inferred diagnosis (ID) according to (6):

$$F(\mathrm{ID}) = \max\left(\left\{ p_0, p_1, \cdots, p_i, \cdots, p_{n_c} \right\} \right). \tag{6}$$

6.3. VSC inference method

VSC inference method, or method with **V**aluation of **S**upported **C**andidates, assigns a single matrix of weighting factors T to the committee of voters. Weighting factors are calculated at training, and they are used later at voting and inference procedures.

$$T = \begin{bmatrix} t_{11}, t_{12}, \cdots, t_{1j}, \cdots, t_{1n_v} \\ t_{21}, t_{22}, \cdots, t_{2j}, \cdots, t_{2n_v} \\ \vdots \\ t_{i1}, t_{i2}, \cdots, t_{ij}, \cdots, t_{in_v} \\ \vdots \\ t_{n_c 1}, t_{n_c 2}, \cdots, t_{n_c j}, \cdots, t_{n_c n_v} \end{bmatrix}, \tag{7}$$

where T is a matrix of weighting factors, t_{ij} is a weighting factor for voting of j^{th} voter for i^{th} candidate, n_c is the number of candidates, and n_v is the number of voters.

Vector of supported candidates G_{VT} is defined according to (8):

$$G_{VT} = \begin{bmatrix} g_{VT0} \\ g_{VT1} \\ \vdots \\ g_{VTi} \\ \vdots \\ g_{VTn_c} \end{bmatrix}, \tag{8}$$

where g_{VTi} is a magnitude of voters support to the i^{th} candidate.
$g_{VTi} = 0$ if none voter votes for i^{th} candidate,
$g_{VTi} = 1$ if either of voters does vote for i^{th} candidate.

Matrix T' is calculated according to (9):

$$T' = f_T(T). \tag{9}$$

Pondered voting vector F is defined according to (10):

$$F = \begin{bmatrix} f_0 \\ f_1 \\ \vdots \\ f_i \\ \vdots \\ f_{n_{dm}} \end{bmatrix}, \tag{10}$$

where f_i is a weighting factor for voting of i^{th} voter, and it is defined according to (11):

$$f_i = \sum_{i=1}^{n_c} t'_{ij} \,, \tag{11}$$

Voting matrix G_T is defined according to (12):

$$G_T = \begin{bmatrix} g_{T11}, g_{T12}, \cdots, g_{T1j}, \cdots, g_{T1n_c} \\ g_{T21}, g_{T22}, \cdots, g_{T2j}, \cdots, g_{T2n_c} \\ \vdots \\ g_{Ti1}, g_{Ti2}, \cdots, g_{Tij}, \cdots, g_{Tin_c} \\ \vdots \\ g_{Tn_{dm}1}, g_{Tn_{dm}2}, \cdots, g_{Tn_{dm}j}, \cdots, g_{Tn_{dm}n_c} \end{bmatrix}, \tag{12}$$

where G_T is voting matrix, and g_{Tij} is a value i^{th} voter vote for j^{th} candidate.

$g_{Tij} = 0$ if i^{th} voter doesn't vote for j^{th} candidate,

$g_{Tij} = 1$ if i^{th} voter does vote for j^{th} candidate.

Counting of votes and assessment of support to individual candidates is defined according to (13):

$$P_D = \left(F^T \cdot G_T\right)^T, \tag{13}$$

where P_D is the vector of support to individual candidates, and p_i is a factor of total support of all voters to i^{th} candidate.

Candidate with highest support p_i is announced as inferred diagnosis (ID) according to (6).

7. EXPERIMENTAL RESULTS

7.1. Set of samples for training and testing of inference methods

VAC and VSC inference methods were tested on the set of 100 samples of transformer faults using stratified k-fold cross validation, where k=3. Distribution of samples with considered diagnoses by training/testing sets is presented in table 5.

Table 5. Distribution of samples with considered diagnoses by training/testing sets.

Diagnosis	Set 1	Set 2	Set 3	Total
NF	3	4	4	11
PD	4	4	4	12
T	17	18	17	52
D	9	8	8	25
Total	33	34	33	100

7.2. Measured parameters

Inference model must be trained to be able to give inference diagnosis. After training, model should be tested. During these procedures some parameters are measured. These parameters allow evaluation of classification properties of the model. These parameters are:

- ca_{psk} - total classification accuracy of method in k subsets,
- ca_{ssck} - total classification accuracy in set of classified samples of k subsets,
- c_m - central approximate accuracy in k subsets, which takes into account both above mentioned accuracies,
- e_{psk} - classification inaccuracy in k subsets,
- e_{ssck} - classification inaccuracy measured in set of classified samples of k subsets,
- c_{res} - percentage of resolved samples in k subsets.

7.3. Measuring results

Measuring results for parameters ca_{psk}, ca_{ssck} and c_{res} measured at model testing are shown in Fig. 2. It is obvious that methods VAC and VSC have significantly higher percentage of resolved samples, compared to all interpretation methods, except Duval triangle method. Classification accuracy ca_{psk} of VSC inference method is better than accuracies of interpretation methods, while accuracy of VAC method is lower then accuracies of the best interpretation methods.

It is important to note that LN method, witch uses the same inference model, has also high accuracy, but its percentage of resolved samples compared to ADS is lower, because it uses different precondition for performing interpretation.

Classification accuracies ca_{ssck} of VSC is equal to it's ca_{psk}, while ca_{ssck} of VAC method is a little bit higher than it's ca_{psk}. N method has the highest value of ca_{ssck}.

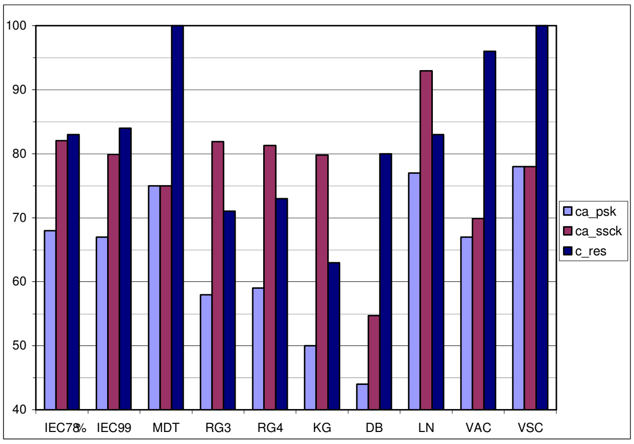

Fig. 2. Comparison of testing classification accuracies and percentage of resolved samples per methods.

Comparing VAC and VSC inference methods, it is obvious that VSC method has better classification properties. Therefore, VAC method will not be used for transformer diagnosis.

Other interpretation methods have significantly lower classification accuracy and percentage of resolved samples compared to VSC method.

It is useful to compare classification parameters of method during training and testing. In this way it is possible to evaluate classification properties of method and confidentially judge its behaviour during operation in reality.

VSC inference method has the same percentage of resolved samples at testing and at training (100 %). Classification accuracy ca_{psk} negligibly decreases (from 79,5 % at training falls to 78 % at testing), and consequently inaccuracy e_{psk} negligibly rises (from 20,5 % at training rises to 22 % at testing), Fig. 3.

Therefore, LN and VSC methods have the best classification properties compared to all other methods, Fig. 2,

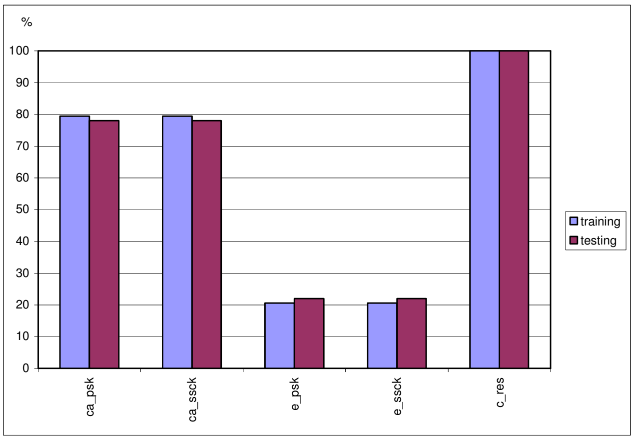

Fig. 3. Comparison of training and testing classification parameters of VSC method.

8. CONCLUSIONS

The automatic diagnosis system is realized implementing known interpretation methods and newly developed inference methods.

The system shows significant classification abilities, with accuracy ca_{psk}=78 %, and with approximate accuracy c_m=80,6 %. If samples with small concentrations of gasses are excluded from analysis according to [9], classification accuracy ca'_{psk} is 86,8%. This is very good result for on-line diagnostics, whereas if some samples couldn't be resolved because of small amount of gas concentrations, after some time, when concentrations increase enough, the system can diagnose the fault before it evolves in failure.

Comparison with interpretation methods shows advantages of new inference method VSC. Besides of better accuracy of this method, it has other interesting and useful features like variable resolution of diagnosis (level of diagnosis).

The developed model is general and it is applied at different levels in the ADS (at the level of interpretation methods - LN method, and at the level of diagnostic system - ADS). Even more, the model is completely general that it can be used to make decision in any kind of election, when voters vote through defined procedure, and when data for training and testing are available.

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