AN ADAPTATIVE NEURO-FUZZY INFERENCE SYSTEM BASED ON DISSOLVED GAS ANALYSIS FOR FAULTS DIAGNOSIS IN POWER TRANSFORMERS

MICHEL B. HELL[1], MARCOS F. S. V. DANGELO[2], GUILHERME I. B. DA FONSECA[1], NEYMARD A. SILVA[3] AND PYRAMO P. COSTA JR.[1]

[1] PPGEE – PUC-Minas – Av. Dom Jos Gaspar, 500, 30535-610
Belo Horizonte, MG – *e-mail:pyramo@pucminas.br*

[2] DCC - State University of Montes Claros, Av. Rui Braga , s/n, 39401-089,
Montes Claros - MG, – *e-mail:marcosv@unimontes.br*

[3] Energetic Company of Minas Gerais (CEMIG), Av. Barbacena, 1200, 30190-924,
Belo Horizonte-MG, – *e-mail:neymard@cemig.com.br*

Abstract: — This paper present a methodology for fault diagnosis in power transformers using an Adaptative Neuro-Fuzzy Inference System . In the development and training of the system was used a real data base of gases concentration in power transformers.

Key-Words: — Fault Detection, Power Transformers , Dissolved Gas Analysis, Fuzzy Systems , Adaptative Systems.

1 Introduction

The transformers are key pieces in power systems. The operative conditions of the system can be highly influenced by variations in the behavior of this equipments. Faults, such as overhathing, arch or partial discharges can cause interruptions in the supply of energy resulting in high costs. This faults are unchained by electric, thermal and mechanics stresses what the transformer is submitted during its operation. During the occurrence of these faults the insulating material of the transformers are degraded, resulting in the generation of gases. The type, the amount and the proportion of these gases depend on the type of degraded material, of the responsible phenomenon for the degradation and the levels of energy involved in the action. This way it is possible to characterize the type and the severity of the fault through the analysis of the gases composition that find dissolved in the insulating oil avoiding the inconveniences of the unexpected loss of the transformer, increasing, with that, the reliability of the system.

Several criteria for the fault diagnosis in transformers starting from the analysis of the dissolved gases in the oil has been developed and it has been used broadly. These criteria, called DGA (Dissolved Gas Analysis), involve several methods, such as the Key Gas Method [7], the Dörnenburg Ratio Method [14], the Rogers Ratio Method [12],[13], among others.

An relatively new approach for transformers diagnosis is the use of fuzzy logic and neural networks. Some diagnosis systems based on these methods are developed with the purpose of diagnosing faults in transformers through the Dissolved Gas Analysis (DGA) in the insulating oil. Dukarm [3] shows as fuzzy logic and neural networks are being used to automate of the standard DGA methods and to improve your usefulness for the diagnosis of lacks. In [4] an approach of artificial neural network (ANN) is presented for diagnosis and detection of faults in power transformers based on the DGA methods. A method in two stages is used to detect faults. Two ANN's are proposed, being one to diagnose the principal types of faults in the transformer (overheating, arch, etc.) and other to identify damages to the cellulose insulating. Huang [15] presents a Evolutionary Fuzzy System Diagnosis (EFDS). In this system the conventional DGA criteria are used to build the initial architecture of the system, including the diagnosis rules and the membership functions of the fuzzy subsets. After this first step, a genetic algorithm is applied so that, with base in previous tests of dissolved gases and your real fault types, the diagnosis rules and the membership functions of the fuzzy subsets are simultaneously adjusted in order to obtain the best performance for the group of samples given. In [11] is presented a neuro-fuzzy hybrid system that combines a ANN with a fuzzy evolutionary expert system , with the purpose of allying the advantages of high learning and high capacity of non lineal map of ANN's with the explicit knowledge represented by the rules of a fuzzy expert system. Hell [10] presents a Fuzzy Neural Network approach (FNN) that use training data sampled in field to increase the diagnosis accurate for a set of equipments. In [5] a Kohonen Neural Network approach is presented. The application of this technique in the solution of the proposed problem is due to the hight capacity patterns classification and low computational cost if compared the other diagnosis systems.

In this work an approach using an Adaptative Neuro-Fuzzy Inference Systems (ANFIS) [9] was used with the purpose of to set the membership functions of expert systems based on real data picked in field and your real faults types, to increase the efficiency of the diagnosis system for a group of equipments.

2 Problem Formulation

Attempts of diagnosing faults in transformers from gases generated after the occurrence of fault started in the decade of 50, having as base the gases collected in the Buchholz relay. In 1956 a detailed assessment of faults from the collected gases was published [1]. Although the importance of the analysis of the gases collected in the Buchholz relay had been unquestionable, the obtained results were usually late, because to have a considerable amount of gases that allow to accomplish the diagnosis, the internal degradation in the transformer it had already reached advanced stage. Just with the arrival of techniques of liquid chromatograph, capable to analyze small oil samples with great precision and sensibility, was possible a new vision of the problem. In 1968 started a regular accompaniment by chromatographic analysis of gases dissolved in the insulating oil and, according to [6], in 1970 over one thousand units of 132, 275 and 400 KV voltage rating were monitored at least annually. The collected data showed that all the transformers, including the slightly loaded, they developed hydrogen and other gaseous hydrocarbons, although in little amount. In 1973 was published [6] a theoretical thermodynamic evaluation of the insulating oils in which suggested that the proportion of each hydrocarbon in the oil varies in agreement with the temperature of its decomposition point. That led for the hypothesis that each gas would reach your maximum concentration degree in a specific temperature. With base in these studies, several methods of diagnosis of faults from dissolved gas analysis in the insulating oil were proposed, among which it is possible to emphasize:

2.1 Key Gas Method

The diagnosis through Key Gas Method is based on the predominance of a certain gas in relation to the Total of Dissolved Combustible Gases (TDCG) in the insulating oil. The TDCG is calculated adding the concentrations of hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2) and carbon monoxide (CO) that find dissolved in the oil. In this method the absolute concentrations (in ppm) and the generation rates (in ppm/dia) of the gases they are used to be determined the type and the intensity certain faults. Based on experimental data was possible to establish concentration limits which, if exceeded in small proportion, it served as first indicative of abnormality. From this limits a four-condition criterion was developed to classify risks to transformers. This criterion use both concentrations for separate gases and the total concentration of all combustible gases, as showed in Table 1.

Table 1. Concentration Limits

		Dissolved Key Gas Concentration Limits (ppm)							
Fault Codition	**Characteristic Fault Condition**	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6	CO	CO_2	TDCG
0	No fault	< 100	< 120	< 35	< 50	< 65	< 350	< 2500	< 720
1	Fault(s) may be present	101 to 700	121 to 400	36 to 50	51 to 100	66 to 100	351 to 570	2500 to 4000	721 to 1920
2	Fault(s) are probably present	701 to 1800	401 to 1000	51 to 80	101 to 200	101 to 150	571 to 1400	4001 to 10000	1921 to 4630
3	Continued operation could result in failure of the transformer	> 1800	> 1000	> 80	> 200	> 150	> 1400	> 10000	> 4630

These values cannot be generalized for the several types of transformers, because older transformers, for example, same apparently free from faults possess high concentrations of gases, already in the newest these concentrations are low. The magnitude of these normal concentrations depends broadly on factors as age, operation conditions, etc., but limits values can be empirically established. Once established the condition of the transformer it is possible to evaluate the probable fault type through the predominance certain gases. These significant gases are called "Key Gases". The following Table 2 indicates these "Key Gases" and its relatives proportions for the for general fault types.

Table 2. Key Gas Method

Fault Type	Characteristic Fault Condition	Relative Proportions (%)						Key Gas
		H_2	CH_4	C_2H_2	C_2H_4	C_2H_6	CO	
1	Oil breakdown (thermal stress)	2	16	0	63	19	0	C_2H_4
2	Cellulose insulation breakdown (related to the aging process)	3	2	0	3	0	92	CO
3	Corona (electric stress)	85	13	0	1	1	0	H_2
4	Arcing (electric stress)	60	5	30	3	2	0	C_2H_2

2.2 Dörnenburg Ratio Method

In 1970, Fallou [7] differentiated between faults of thermal and electrical origin by comparison pairs of characteristic gases, with approximately equal solubilities and diffusion coefficients. This method was considered promising, because it eliminated the effect of the volume of oil of the transformer, could be applied so much to units with great volumes of gases generated as to small units. From these considerations and of experiences it was obtained 4 concentration ratios of pairs of particularly useful gases [14], that are presented below:

1. $\frac{CH_4}{H_2}$ $\qquad \frac{\text{Concentration of methane}}{\text{Concentration of hydrogen}}$

2. $\frac{C_2H_2}{C_2H_4}$ $\qquad \frac{\text{Concentration of acetylene}}{\text{Concentration of ethylene}}$

3. $\frac{C_2H_6}{C_2H_2}$ $\qquad \frac{\text{Concentration of etano}}{\text{Concentration of acetileno}}$

4. $\frac{C_2H_2}{CH_4}$ $\qquad \frac{\text{Concentration of acetylene}}{\text{Concentration of methane}}$

From experimental data was obtained a relationship between typical faults and ranges of values related to the above ratios, generating, like this, a criteria for the diagnosis of faults. These ranges are shown in the Table 3. The following rules are necessary for the application of the ratios concentration described above in the diagnosis process:

1. An only ratio can just be used in the diagnosis if the concentration of one of the two gases of the relationship is twice larger than the value limits shown in the Table 1;

2. Several ratios can be used together in the diagnosis if at least one of the first two ratios can be used alone, in agreement with the rule above and, at least a gas of those whose concentrations are formed by other ratio, exceed the limiting value in Table 1;

3. In the case of transformers with gas cushions (mainly nitrogen) above the oil level, the limiting values quoted in the Table 3 can be applied only to a limited extent. If the oil volume and gas cushion are known, the limiting values can be calculated.

This diagnosis method may be used only with extreme caution if the dissolved gases are originated from a fault that are not more present for some time, because several decomposition gases travel to the surface of the oil, expanding in the tank of the transformer and escape to atmosphere, what can distort the diagnosis. Monoxide and dioxide of carbon are typically related to the process of decomposition of the solid isolation, and they are not used in the characteristic ratios. The ranges of characteristic values for extracted gases from the oil and for free gases (such as contained them in the Buchholz relay and the ones that form the gas cushion) related with the faults types are presented in the tables 3 and 4, respectively.

Table 3. Ranges of characteristic values for ratios of gases dissolved in transformer oil

Ratio of Concentations of Dissolved Gases	$\frac{CH_4}{H_2}$	$\frac{C_2H_2}{C_2H_4}$	$\frac{C_2H_6}{C_2H_2}$	$\frac{C_2H_2}{CH_4}$
Type of Characteristic Faults				
Termal decomposition (hot spots)	> 1.0	< 0.75	> 0.4	< 0.3
Corona	< 0.1	*	> 0.4	< 0.3
Electrical discharges (except corona)	>0.1 e <1	> 0.75	< 0.4	> 0.3

* Not significant

Table 4. Ranges of characteristic values for ratios of free gases (relay or cushion) in transformer

Ratio of Concentations of Dissolved Gases	$\frac{CH_4}{H_2}$	$\frac{C_2H_2}{C_2H_4}$	$\frac{C_2H_6}{C_2H_2}$	$\frac{C_2H_2}{CH_4}$
Type of Characteristic Faults				
Termal decomposition (hot spots)	> 0.1	<1.0	> 0.2	< 0.1
Corona	< 00.1	*	> 0.2	< 0.1
Electrical discharges (except corona)	> 0.01 e < 0.1	>1.0	< 0.2	> 0.1

* Not significant

A diagnosis is appropriately confirmed if two or more of the used ratios are within the ranges of values are typical for the same type of fault.

2.3 Rogers Ratio Method

In 1975 a statistical study in more than ten thousand gas analysis in transformers [12] showed that certain types of faults conditions could be differentiated within more detailed ranges and combinations of ratio of gases. This was confirmed by internal examination of a certain number of suspect transformers together with units destroyed in faults, as well as for the study of hot spots likely to be found in transformers under operational conditions. So, was proposed a refined code using three ratios diagnosing a larger number of faults. The use of the code facilitated computational programming in the development diagnosis systems. To establish the identification of current faults a study was accomplished in a hundred groups of oil analysis extracted of transformers with known fault types in order to evaluate the probable temperature in the which the ratios indicate significant changes. Based on the result of these studies and theoretical assessment, new changes of ratios values for electric and thermal faults were then obtained. To help in the understanding of the technique a table were organized to indicate a more rational progression of faults, resulting the code described in the Table 5.

Table 5. Code for analysis of dissolved gases in mineral oil

Code of ranges ratios		Ratios of characteristic gases $\frac{C_2H_2}{C_2H_4}$	$\frac{CH_4}{H_2}$	$\frac{C_2H_4}{C_2H_6}$
< 0.1		0 (L)	1 (L)	0 (L)
0.1 - 1.0		1 (M)	0 (M)	0 (L)
1.0 - 3.0		1 (M)	2 (H)	1 (M)
> 3.0		2 (H)	2 (H)	2 (H)
Fault Code	**Characteristic fault type**			
0	No fault	0 (L)	0 (M)	0 (L)
1	Low temperature thermal fault < 150º	0 (L)	0 (M)	1 (M)
2	Low temperature thermal fault 150º - 300º	0 (L)	2 (H)	0 (L)
3	Medium temperature thermal fault 300º - 700º	0 (L)	2 (H)	1 (M)
4	High temperature thermal fault > 700º	0 (L)	2 (H)	2 (H)
5	Low energy partial discharges	0 (L)	1 (L)	0 (L)
6	High energy partial discharges	1 (M)	1 (L)	0 (L)
7	Low energy discharges	1-2 (M-H)	0 (M)	1-2 (M-H)
8	High energy discharges	1 (M)	0 (M)	2 (H)

In the approach proposed in this work the Rogers ratio method is used to build the initial architecture of the membership functions of the fuzzy subsets in the ANFIS [10]. This method uses three relationships of gases, obtained through chromatographic analysis. In the fuzzy model, each set is associated with each one of the input ratios, with defined threshold values in agreement with the original DGA method, as can be seen in the figures presented to proceed, where Figure 1 , 2 and 3 shows the ratios $\frac{CH4}{H2}$, $\frac{C_2H_2}{C_2H_4}$, and $\frac{C_2H_4}{C_2H_6}$, respectively. The fuzzy rules are derived of the code presented in the Table 1 and are applied to obtain the uncertain factors for the diagnosis based on the Rogers method. To assure the consistence with the Rogers method, the membership functions of the intervals fuzzy are defined as 0.5 of the correspondents " crisp " intervals limits [15]. To the obtaining of a diagnosis, the values of the gases ratios are applied to the Fuzzy Inference System (FIS), where the pertinence functions associated with the fuzzy sets, shown previously, are applied to the considered variables. The output of the fuzzy system is one of the types of faults presented in the Table 5, where L, M and H are the fuzzy subsets **Low**, **Medium** and **High**, respectively.

Figure 1. Ratio Methane / Hidrogen

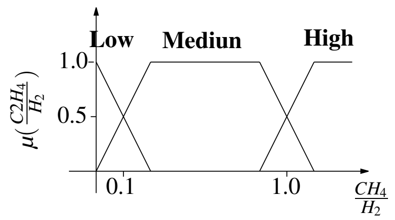


Figure 2. Ratio Acetylene / Ethylene

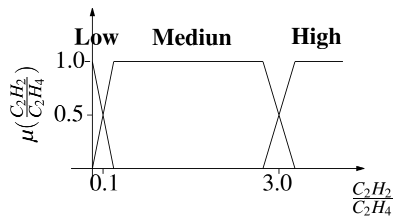
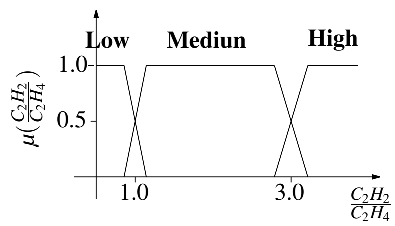


Figure 3. Ratio Ethylene / Ethane



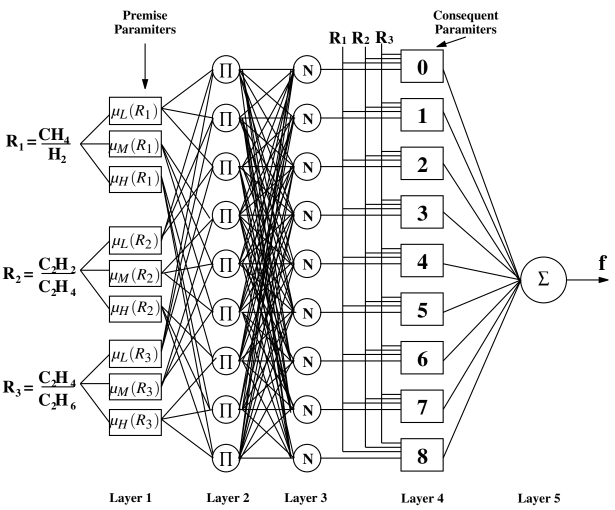
3 The Adaptative Neuro-Fuzzy Inference System

The proposal of this work is to improve the efficiency of the fuzzy inference system being used the technique of neuro-adaptive learning in the adjustment of the membership functions described previously, for these functions to have better acting for a group of transformers.

The basic idea behind these neuro-adaptive learning techniques is very simple. These techniques provide a method for the fuzzy modelling procedure to learn information about a data set containing real samples and its current fault types given by [2], in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. This learning method works similarly to that of neural networks.

Then the ANFIS architecture of the proposed system is presented in the Figure 4.

Figure 4. ANFIS Structure



According to [8], the node functions in the same layer are of the same function family as described below:

Layer 1: Every node in this layer is a square node that represents the membership function of the linguistic label (S , M and L as presented in the Figures 1,2 and 3) and it specifies the degree to which the given inputs R_i $(i = 1, \cdots, 3)$ satisfies the linguistic labels.

Layer 2: Every node in this layer is a circle labelled $\prod$ which multiplies the incoming signal and sends the product out. Each node output represents the firing strength of a rule.

Layer 3: Every node in this layer is a circle labelled N. The ith node calculates the ratio of the ith rule's firing strength to the sum of all rules' fire strengths:

$$\overline{\omega}_i = \frac{\omega_i}{\sum_i \omega_i} \qquad i = 1, \cdots, 3.$$

where ω_i is the output of the layer 2. For convenience, outputs of this layer will be called *normalized firing strength*.

Layer 4: Every node i in this layer is a square node with a node function:

$$O_i^4 = \overline{\omega}_i f_i = \overline{\omega}_i (p_i R_1 + q_i R_2 + s_i R_3 + \tau_i)$$

where $\overline{\omega}_i$ is the output of layer 3, and $\{p_i, q_i, s_i, \tau_i\}$ is the parameter set.

Layer 5: The single node in this layer is a circle labelled $\sum$ that computes the overall output as the summation of all incoming signals.

The system developed in this work was trained with 40 samples and it was tested using 435 samples of a real data base. The results are presented in the Table 6.

Table 6. Results

Input Data	No. of Samples Tested			% Accurate	
	Correct Diagnosis	FIS	ANFIS	FIS	ANFIS
Sample related to Type Fault 0	7	5	7	71%	100%
Sample related to Type Fault 1	34	37	34	92%	100%
Sample related to Type Fault 2	104	100	104	96%	100%
Sample related to Type Fault 3	20	19	20	95%	100%
Sample related to Type Fault 4	43	48	43	90%	100%
Sample related to Type Fault 5	0	3	0	100%	100%
Sample related to Type Fault 6	28	29	28	97%	100%
Sample related to Type Fault 7	143	131	143	92%	100%
Sample related to Type Fault 8	70	77	70	91%	100%
TOTAL ACCURATE OF THE SYSTEMS				91,46%	100,00%

4 Conclusions

The use of ANFIS technique has been proved to be an accurate fault detection in powers transformers, and the benefits of the early detection and monitoring of incipient faults are proven and are increasingly applied to current and emerging maintenance concepts.

5 Acknowledgements

The authors acknowledgements the CEMIG for yielding the database of the CEMIG and Eng. Álvaro J.

Martins (CEMIG), Eng. Ronald Moura (CEMIG) by help in the development of work, and to the National Council for Scientific and Technological Development of Brazil - CNPq-Brazil, by partial financing of this work.

References:

[1] V. H. Howe A. M. Wilson, L. Massey. Identity and significance of gases collected in buchholz protectors. *M. V. Gazette*, May 1956.

[2] ANSI/IEEE Std C57.104-1991. Ieee guide for interpretation of gases generated in oil-immersed transformers. *IEEE Power Engineering Society*, 1992.

[3] J. J. Dukarm. Transformer oil diagnosis using fuzzy logic and neural networks. *Canadian Conference on Electrical and Computer Engineering*, 1:329–38, 1993.

[4] Y. Zang et al. An artificial neural network approach to transformer fault diagnosis. *IEEE Trans. on Power Delivery*, 11(4):1836–41, October 1996.

[5] M. B. Hell M. F. S. V. D'Angelo N. A. Silva G. I. B. da Fonseca, P. P. Costa Jr. Power transformer fault diagnosis based on dissolved gas analysis using a Kohonen neural network approach in a real data base. *V IEEE Conference on Industry Aplications,*, Salvador-Brazil, 2002.

[6] W. D. Halstead. A thermodynamic assessment of the formation of gaseous hydrocarbons in faulty transformers. *Journal of the Institute of Petroleum*, 59(569):239–41, September 1973.

[7] B. Fallou F. Viale R. R. Rogers I. Davies, E. Drnerburg. Aplication of physico-chemical methods of analysis to the study of deterioration in the insulation of electrical apparatus. *CIGRE Report 15-07*, 1970.

[8] Jhy-Shing R. Jang. Anfis: Adaptative-network-based fuzzy inference system. *IEEE Transaction on Systems, Man and Cibernetics*, 23(3):665–85, May 1993.

[9] Jyh-Shing R. Jang. *Neuro-fuzzy and soft computing: a computational approach to learning and machine intelligence*. Upper Saddle River: Prentice-Hall, USA, 1997.

[10] M. B. Hell M. F. S. V. D'Angelo, P. P. Costa Jr. Power transformer fault diagnosis based on dissolved gas analysis using a fuzzy neural network approach in a real data base. *2nd WSEAS International Conference on Soft Computing, Simulation and Manufaturing Systems,*, Cancun-Mexico, 2002.

[11] Z. Wang P. J. GRIFFIN, Y. LIU. Neural net and expert system diagnose transformer faults. *IEEE Computer Aplications in Power*, 13(1):50–55, January 2000.

[12] R. R. Rogers. UK experience in the interpretation of incipient faults in power transformers by dissolved gas-in-oil chromatographic analysis. *Doble Client Conference, Paper 42 AIC 75*, 1975.

[13] R. R. Rogers. IEEE and IEC codes to interpret incipient faults in transformers, using gas-in-oil analysis. *IEEE Trans. Elect. Insul.*, EI-13(5):348–54, October 1978.

[14] E. Dornenburg W. Strittmatter. Monitoring oil-cooled transformers by gas analysis. *Brown Boveri Review*, 5(61):238–47, May 1974.

[15] C. L. Huang Y. C. Huang, H. T. Yang. Developing a new transformer fault diagnosis system through evolutionary fuzzy logic. *IEEE Trans. on Power Delivery*, 12(2):761–67, April 1997.