Power Transformer Fault Diagnosis Based on Dissolved Gas Analysis Using a Fuzzy Neural Network Approach in a Real Data Base

Michel B. Hell[1] , Marcos F. S. V. D`Angelo[2] and Pyramo P. Costa Jr.[1]
[1] Programa de Pós-graduação em Engenharia Elétrica
Pontifícia Universidade Católica de Minas Gerais
Av. Dom José Gaspar, 500, Belo Horizonte-MG, CEP 30535-610, Brasil

[2] Departamento de Ciência da Computação
Universidade Estadual de Montes Claros
Av. Rui Braga , s/n, Montes Claros - MG, CEP 39401-089, Brasil

Abstract: - This paper present a methodology for power transformers diagnosis using a fuzzy neural network approach. In the development of the system and neural network training was used a real data base of gases concentration in power transformers supplied by Energetic Company of Minas Gerais (*CEMIG)*.

Key-Words: - Power Transformers, Fault Detection, Neural Networks, Fuzzy Set.

1 Introduction

In this paper is development a methodology for fault detection and isolation (FDI) in power transformers using fuzzy neural network approach. The development of this type of techniques have received a large attention during the last decades, as well as the diagnosis in dynamic systems in general. The majority of the fault diagnosis systems are based on models, where many variable and parameters of the system are taken in account so that can construct a detailed mathematical system's model. Once the dynamic behavior of the system was adjusted, is possible, theoretically, to diagnose faults through variations of the parameters. The FDI technique based on observers is an approach largely used that uses models. In this technique, signals, known as residues, are generated by observers, where the fault is detected when the predetermined levels of threshold are reached. In [1] is showed an inclusive research of project methods for FDI that, although projected for linear systems, can be used, in many cases, in non-linear problems. In [2] and [3] is proposed robust filters design to fault detection in dynamic systems and [4] propose a similar technique, however optimal stochastic properties for FDI are certain. In [5] is considered the FDI problem using thresholds equal to zero or near of zero, with that, a number of different FDI problems with separate disturbances is formulated. An relatively new approach for systems modeling is the use of fuzzy logic and neural networks. These methods are attractive for doesn't request explicit mathematical models of the plant to be monitored.

Some systems using these methods is being developed with the purpose of diagnosing faults in transformers through the analysis of gases dissolved in the insulating oil (DGA). Dukarm [6] 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 [7] 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 [8] 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 [9] 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.
Recent studies [10] showed, the existence of, relationships between the dissolved gases in the oil and certain physical-chemical greatness of the insulating oil, such as color, density, neutralization index, interfacial tension, humidity, etc.
In this work, an approach using fuzzy neural network will be applied to the problem of fault diagnosis using the DGA methods, especially the Rogers ratio method, however is our future goal to develop techniques that make possible to evaluate the state of the operative conditions (fault conditions) of the transformers starting from the analysis of the characteristics physical-chemistries of the oil, that can be obtained in routine sampling. Intends to obtain a correlation between the results obtained through DGA and those starting from the characteristics physical-chemistry of the insulating oil in the indication of faults in the transformer.
The objective of this study is to verify the possibility to use the results of routine sampling of smaller cost, in the process of fault diagnosis in the power transformers.

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 [11]. 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 [12], 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. HALSTEAD published in 1973 [12] a theoretical study was published with the 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 your 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 certain gas with relationship 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), etano (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2) and carbon monoxide (CO) that one find dissolved in the oil. In that 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. These faults are related with the " key gases " in the following way:

H_2 ⋗ Corona (electric stress)

CH_4 & C_2H_6 ⋗ Low temperature oil breakdown (thermal stress)

C_2H_4 ⋗ High temperature oil breakdown (thermal stress)

C_2H_2 ⋗ Arcing (electric stress)

CO & CO_2 ⋗ Cellulose insulation breakdown (related to the aging process)

In the transformers in service the oil insulating always contains considerable concentrations of carbon dioxide and carbon monoxide, certain amount of hydrogen and small concentrations of light hydrocarbons. These gases are generated, even certain levels limit, due to the natural process of aging of the insulating materials. If these levels limit of concentrations could be attributed for each gas, which if exceeded in small proportions (5 or 10%) they served as first indicative of an abnormality, leading, thus, to exams more detailed, such levels could be considered as “normal”. 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.
Dörnenburg [13], based on experimental data identified that if the concentrations of related gases in the Table 1 be not exceeded after few years of operation of the transformers, indicates that they are free from faults.

Table 1: Concentration limits

Hydrogen	200 ppm
Methane	50 ppm
Etano	15 ppm
Ethylene	60 ppm
Acetylene	15 ppm
Carbon monoxide	1000 ppm
Carbon dioxide	11000 ppm

If two or more gases exceed the concentrations limit shown, the transformer should be considered as suspect.

2.2 Dörnenburg Ratio Method

In 1970, Dörnenburg [14] 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 [13], that are presented below:

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

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

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

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

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 flaws. These ranges are shown in the Table 2.

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 2 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 2 and 3, respectively.

Table 2: Ranges of characteristic values for ratios of gases dissolved in transformer oil

Ratios of Concentrations of Dissolved Gases	$\frac{CH_4}{H_2}$	$\frac{C_2H_2}{C_2H_4}$	$\frac{C_2H_6}{C_2H_2}$	$\frac{C_2H_2}{CH_4}$
Types of Characteristic Faults				
Thermal decomposition (hot spots)	> 1	< 0.75	> 0.4	< 0.3
Corona	< 0.1	*	> 0.4	<0.3
Eletrical discharges (except corona)	< 1 > 0.1	> 0.75	< 0.4	> 0.3

* Not significant

Table 3: Ranges of characteristic values for ratios of free gases (relay or cushion) in transformer

Ratios of Concentrations of Free Gases	$\frac{CH_4}{H_2}$	$\frac{C_2H_2}{C_2H_4}$	$\frac{C_2H_6}{C_2H_2}$	$\frac{C_2H_2}{CH_4}$
Types of Characteristic Faults				
Thermal decomposition (hot spots	> 0.1	< 1.0	> 0.2	< 0.1
Corona	< 0.01	*	> 0.2	<0.1
Eletrical discharges (except corona)	< 0.01 > 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 [15] a refined code from the ranges of gases was proposed using the four ratios shown previously, however diagnosing a larger number of faults. The use of the code facilitated computational programming in the development diagnosis systems.
Statistical study in more than ten thousand gas analyses in transformers [16] 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.
To establish the identification of current faults a study was accomplished in a hundred groups of oil analyses extracted of transformers with known fault types [16] 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.
Due to the fact that the ratio etano/methane to indicate a limited range of decomposition temperatures, but not assist in further faults identifications, it was deleted. It was then considered that the use of only three ratios would simplify the interpretation. To help in the understanding of the technique the tables they were reorganized to indicate a more rational progression of faults, resulting the code described in the Table 4.
This code was included in the document IEC 10A 53 and it became recommended by IEEE and IEC as main code for interpretation of incipient faults in transformers, using analysis of gases in the oil. In this work this method will be used as base for the construction of the FNN proposed, as presented in the next section.

3 Structure of Fuzzy Neural Network (FNN) in the Fault Detection of Power Transformers

A structure of FNN, described by [17], have been developed for power transformers fault detection. The adoption of a FNN structure approach aims at development of an architecture that can localize abrupt and incipient faults correctly, from only single abrupt faults symptoms, and be easily trained.

Table 4: 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 FNN. This method, as described previously, uses three relationships of gases, obtained through chromatographic analyses.
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 CH_4/H_2 , C_2H_2/C_2H_4 ,AND C_2H_4/C_2H_6 , respectively.
The fuzzy rules are derived of the code presented in the Table 4 and are applied to obtain the certain 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 [6].
The architecture of the system diagnosis proposed, differently of the presented in [17], have only one FNN, as can be seen in the Figure 4. This is due to the fact that the Rogers ratio method doesn't produce diagnoses with more than a simultaneous fault.
The proposed system can be divided in two layers: a fuzzy layer, and an output layer.

Figure 1: Ratio methane/hidrogen

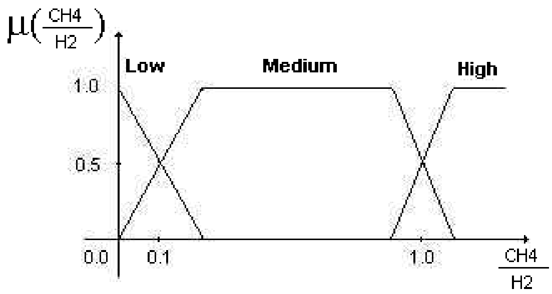


Figure 2: Ratio acetylene/etilene

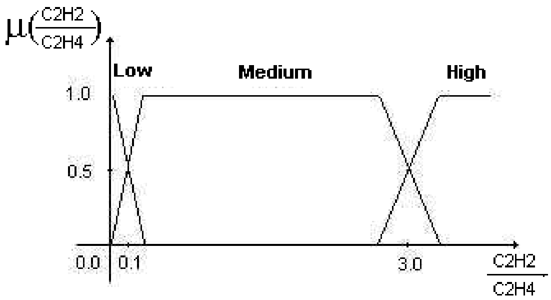
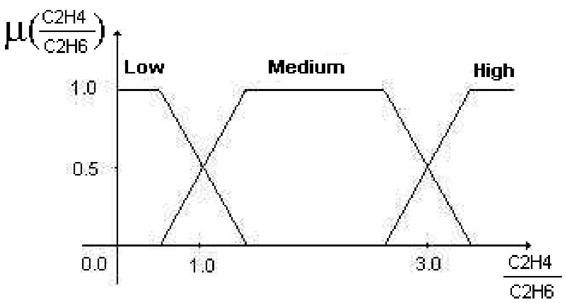


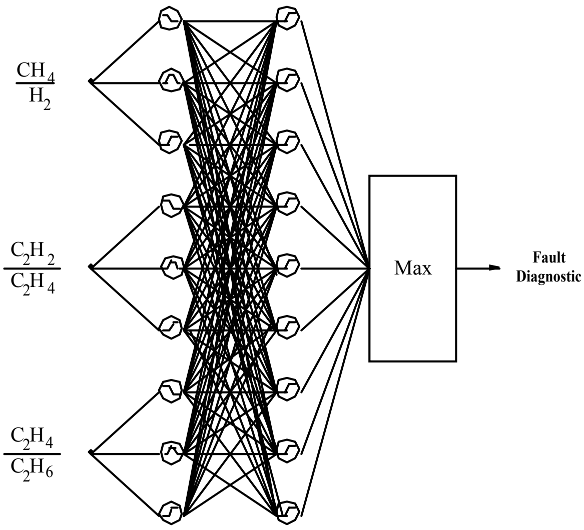
Figure 3: Ratio etilene/etano



To the obtaining of a diagnosis, the values of the ratios of gases are applied to the fuzzy layer, where the pertinence functions associated with the fuzzy sets, shown previously, are applied to the considered variables. The output of the fuzzy layer will be composed by a vector of nine positions, that represents the pertinence of the input data in your respective fuzzy sets " Low ", Medium " and " High ".

This output is, then, fed in a conventional Neural Network (NN) with only one layer. This layer, called output layer, presents nine neurons, the first neuron represent the normal condition and the others representing, each one, a fault type. In each one of them is wanted to obtain value 1 in the neuron that represents the fault type to be diagnosed, and 0's in all the others.

Figure 4 : Proposed Diagnosis System



For that the NN is trained to produce a 1 in the correct position of the output vector and to complete the rest of the output vector with 0's. However, input values different from the used in the training result in the creation of values different from 0's and 1's. With that, is had as final diagnosis of the system the fault type associated to the neuron that possesses larger output value.

In the Table 5 is presented the results analysis obtained from comparison between of output of FNN and diagnosis in real data base for an sample of 400 patterns.

Table 5: Results

Event	Occurrence index
False fault detection	0 %
Undetected fault	0 %
Correct detection	100%

4 Conclusion

The use of fuzzy neural network 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.

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