Artificial Neural Network Application In Estimation Of Dissolved Gases In Insulating Mineral Oil From Physical-Chemical Datas For Incipient Fault Diagnosis

Fábio R. Barbosa, Otacílio M. Almeida, Arthur P. S. Braga, Cícero M. Tavares, Márcio A. B. Amora, Francisco A. P. Aragão, Paulo R. O. Braga, Sergio S. Lima

Departamento de Engenharia Elétrica,
Universidade Federal do Ceará
Fortaleza-CE, BRASIL
E-mails:{fabio, otacilio, arthurp, cicero, marcio, aldinei, proberto, sergio}@dee.ufc.br

Abstract— **In this paper, Artificial Neural Networks are used to solve a complex problem concerning to power transformers and characterized by non-linearity and hard dynamic modeling. The operation conditions and integrity of a power transformer can be detected by analysis of physical-chemical and chromatographic isolating oil, allowing establish procedures for operating and maintaining the equipment. However, while the costs of physical-chemical tests are smaller, the chromatographic analysis is more informative. This work presents an estimation study of the information that would be obtained in the chromatographic test from the physical-chemical analysis through Artificial Neural Networks. Thus, the power utilities can achieve greater reliability in the prediction of incipient failures at a lower cost. The results show this strategy to be a promising, with accuracy of 100% in best cases. The application in the thermal fault diagnosis presents more than 91% accuracy in best cases.**

Keywords- Chromatograph, Physical-chemical, Incipient Failures, Transformers, Artificial Neural Network.

I. INTRODUCTION

The dielectric quality of the transformer insulating oil, and the incipient failures of thermal and electrical type of this equipment, can be determined from physical-chemical and chromatograph tests [4, 7, 8, 14]. These tests are important to keep the integrity of the transformers. In the meantime, while the costs of the physical-chemical tests are lower, the chromatograph one is more informative. [2, 3, 12, 19].

There are, in the technical literature, papers which point to the correlation between these two types of tests. [9, 5, 14, 18], and this article aims at methodology to explore this co-relation when estimates the concentration of gases dissolved in insulating oil (normally obtained by chromatograph test) in function of physical-chemical characteristics of the sample. This proposal, thus, brings economic reduction in the information extractions relevant to foresee incipient failures of transformers [2, 3, 7, 8, 12, 17, 18].

The relation between the physical-chemical measures and the gases concentration is set in this paper through Artificial Neural Networks (ANN) [6, 16] which from examples learn how to make linear or no-linear mappings, considered universal approximators[6].

This document is organized as it follows. The Section II makes comments about the relation between the measures of physical-chemical and chromatograph tests. The Section III talks about the estimative proposal of dissolved gases using ANN. The Section IV deals with the definition of the most influent physical-chemical attributes in the dissolved gases estimative. The results obtained are analyzed in Section V, and the conclusions in Section VI.

II. RELATION BETWEEN PHYSICAL-CHEMICAL MEASURES TESTS AND CHROMATOGRAPH

Some researches look for associating the abnormal dielectrics characteristics of the oil to appearance of internal failures [5, 9, 14, 18]. These abnormalities can be related to the presence of free radicals and of oxygen dissolved under copper catalytic effect, starting the process of oil degradation in the measure of its aging. [5, 18].

Tests with spectroscopy dielectric methods present co-relation between the aging of oil and the loss factor (tan δ). Samples with alternate physical-chemical characteristics present loss factor dependent on temperature, according to the figure 1 [14].

Studies of [15], demonstrate that the oil conductivity, supplement parameter to breakdown voltage, keep one relation ascendant with the temperature.

It is known that the mechanism of gases formation inside transformers follows a thermodynamic model which associates the rate of gases formation to temperature around the neighborhood of the local where occur the failure. [7, 8].

This information indicates that there is a possibility of getting relations between physical-chemical and chromatographs characteristics. However, because there is no a classical way to establish these relations, the application of methods based on computational intelligence, like ANN, can provide satisfactory results concerning to insulation behavior of the transformer liquid [9].

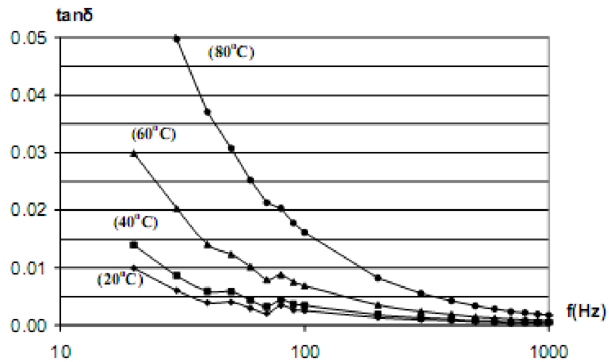

Figure 1. Spectroscopy dielectric of aged insulating oil [14].

III. Estimation of Dissolved Gases Using One Artificial Neural Network

Considering the results obtained in [14], were definite the physical-chemical characteristics which influence in the quality of insulating oil. The vector of input to be applied to ANN is constituted by the certain elements: Acidity, Breakdown Voltage, Water Content, Interfacial Tension, Density and Oil Power Factor.

The estimation of dissolved gases is obtained in the output of the neural network. The estimated gases are necessaries to make the diagnostic of incipient failures in transformers [1, 2, 7, 8, 13, 17, 20]. Thus, the concentrations of the followed gases were estimated: Hydrogen (H_2), Carbon Monoxide (CO), Carbon Dioxide (CO_2), Methane (CH_4), Ethane (C_2H_6), Ethylene (C_2H_4) and Acetylene (C_2H_2).

It was conceived one ANN to each gas to be estimated with just one neuron of output. Therefore, the seven neural networks give the associate linking between the physical-chemical measures of input and the dissolved gases in oil.

Tests were done to the estimation of gases dissolved in the oil of the transformer from physical-chemical analyze with two architecture of ANN: (i) Network MLP (Multi Layer Perceptron), with algorithm of training Levenberg-Marquardt [3] and (ii) Network RBF (Radial-Basis Function) with incremental strategy of increase of new neurons in the hidden layer to better mapping [3, 12].

IV. Definition of the Most Influential Physical-Chemical Attributes in Estimation of Dissolved Gas

In estimation of dissolved gas, appears, parallel, the question of identification which physical-chemical characteristics are relevant to association with dissolved gases. To this task, it is used one algorithm known by exhaustive search related to one adaptive system of inference neuro-fuzzy (ANFIS) [10, 11].

This type of inference system uses datas of input and output to construct one fuzzy system where the functions of relevance are adjustable allowing that the system learns from its own datas of model.

One structure of parameterized model is considered as hypotheses, relating the input relevance functions and the rules to output relevance functions. The input and output datas are used to modify the relevance functions parameters according to the criteria of error, during one training process.

To selection of the most influential attribute among the six inputs to estimation of dissolved gases it is necessary the construction of six ANFIS. The input and output datas are organized in a way that the first half is designed to the training while the second half is lead to the validation. The overfitting was avoided when there is the same dimension of error values of training and validation.

The most influential input resulting from the exhaustive search is the one which presents the lowest error value of training and error value of validation accordingly.

In the meantime, it can there be more than one physical-chemical influential attribute in the relation with the dissolved gas in oil. The exhaustive search, then, constructs 15 models ANFIS relating the attributes in pairs to define what models present the lowest values of error of training with validation error accordingly.

In case of a minimum error of training and validation is reduced significantly, the system presents two influential inputs. In the attempt of picking up more than one influential input, the strategy constructs 20 models ANFIS, with the attributes organized in trios, and the errors of training and validation are analyzed. If they do not present improvement, then just two inputs are more influential and necessaries to a good estimation.

A. *Most influential attributes*

The application of the algorithm of exhaustive search to definition of the most influential input in the dissolved hydrogen got the ANFIS model composition of the table I which points to interfacial tension as most influential attribute in the presence of dissolved hydrogen. The errors of training and validation imply the existence of overfitting indicating that is possible to test more inputs: The table II considers the two and the three most influential inputs.

TABLE I. Exhaustive Search Result – Hydrogen

ANFIS Model (Input)	Training error	Validation error
Acid	140,52	173,73
Breakdown Voltage	140,76	172,95
Water content	140,84	173,00
Interfacial tension	138,35	170,97
Density	139,23	171,05
Power factor	141,92	173,57

From table II, it occurs the falling in error values when another attribute is added. In case of three attributes as input, the training gets better, but the validation error increase, this means a possible sign of overfitting. At first, the water content attribute can improve the estimation, but with loss of generalization indicating that it is not vantage to add more inputs.

TABLE II. MOST INFLUENTIAL ATTRIBUTES - HYDROGEN.

ANFIS Model– Input	Training error	Validation error
Breakdown Voltage– I. Tension	131,74	169,97
Breakdown Voltage – I. Tension – Water Content	126,24	186,42

Following the same algorithm presented to the hydrogen, the exhaustive search was applied to monoxide and carbon dioxide, methane, ethylene ethane and acetylene. The results are in table III to VIII as it follows.

TABLE III. MOST INFLUENTIAL ATTRIBUTES - CARBON MONOXIDE.

ANFIS Model– Input	Training error	Validation error
Power Factor	255,26	247,06
Power Factor– Density	218,31	254,03
P. Factor – I. Tension – Density	172,85	531,86

TABLE IV. MOST INFLUENTIAL ATTRIBUTES - CARBON DIOXIDE.

ANFIS Model– Input	Training error	Validation error
Density	2052,51	2224,17
Interfac. Tension – Density	1833,80	2413,57
Break. Voltage – I. Tension – Density	1588,79	2706,55

TABLE V. MOST INFLUENTIAL ATTRIBUTES - METHANE.

ANFIS Model– Input	Training error	Validation error
Power Factor	30,84	39,33
Power Factor – Density	27,61	38,62
P. Factor – Density – Break. Voltage	23,20	77,73

TABLE VI. MOST INFLUENTIAL ATTRIBUTES - ETHYLENE.

ANFIS Model– Input	Training error	Validation error
Interfacial Tension	41,20	57,06
Power Factor – Interf. Tension	37,27	57,55
P. Factor – I. Tension – B.Voltage	32,87	101,71

TABLE VII. MOST INFLUENTIAL ATTRIBUTES - ETHANE.

ANFIS Model– Input	Training error	Validation error
Power Factor	52,28	39,52
Power Factor – Density	36,99	32,88
P. Factor – Density – Breakdown Voltage	25,82	69,54

TABLE VIII. MOST INFLUENTIAL ATTRIBUTES - ACETYLENE.

ANFIS Model– Input	Training error	Validation error
Density	165,83	262,64
Breakdown Voltage – Density	159,03	255,92
Interfac. Tension– Density – Breakdown Voltage	150,02	256,77

The results regarding acetylene reveal much tendency to overfitting, probably because of lack of datas. The strategy presents difficulties to develop succeed models to the objective proposed of establishing the most influential attributes to the dissolved acetylene.

V. RESULTS ANALYZES

From the database of chromatography and physical-chemical analyzes were used 251 samples, extracted from [3], to fulfill the training stages, validation and developed Neural Networks tests.

A. Dissolved Gases Estimation

In ANN project, the sets of training, validation and test present, respectively, 140, 60 and 51 samples and been the output expected to the process of training the diagnostic supplied in the technical report of the expert responsible for physical-chemical analyze of insulating oil.

The training stage of projected Neural Networks uses information obtained in Section IV of this article. The Networks were tested with 2 and 3 attributes of input. The tables IX to XV present the values of percentage of hit to the MLP trained by the algorithm Levenberg-Marquardt (identified by LM) and the Network RBF Incremental (identified by RBF-Inc) in function of neuron numbers used in the hidden layer in the set of datas of training, validation and test.

TABLE IX. HIT PERCENTAGE OF NEURAL NETWORKS TO ESTIMATION OF HYDROGEN.

Training Algorithm	Number Neurons Hidden Layer	Correct Diagnosis (%) 2 attributes / 3 attributes		
		Training	Validation	Test
LM	***5***	98,57 / 98,57	100,00 / 100,00	100,00 / 100,00
RBF-Inc	***5***	98,57 / 94,29	98,33 / 90,00	100,00 / 94,12
LM	***15***	98,57 / 98,57	98,33 / 95,00	100,00 / 98,04
RBF-Inc	***15***	98,57 / 98,57	100,00 / 100,00	100,00 / 100,00
LM	***25***	98,57 / 98,57	98,33 / 93,33	98,04 / 98,04
RBF-Inc	***25***	98,57 / 98,57	100,00 / 100,00	100,00 / 100,00
BEST SETTING		MLP-LM – 5 neurons – 2 attributes		

TABLE X. HIT PERCENTAGE OF NEURAL NETWORKS TO ESTIMATION OF CARBON MONOXIDE.

Training Algorithm	Number Neurons Hidden Layer	Correct Diagnosis (%) 2 attributes / 3 attributes		
		Training	Validation	Test
LM	***5***	100,00 / 100,00	98,33 / 100,00	94,12 / 100,00
RBF-Inc	***5***	100,00 / 100,00	100,00 / 100,00	100,00 / 100,00
LM	***15***	100,00 / 100,00	98,33 / 98,33	96,08 / 98,04
RBF-Inc	***15***	100,00 / 100,00	100,00 / 100,00	100,00 / 100,00
LM	***25***	100,00 / 100,00	98,33 / 98,33	96,08 / 96,08
RBF-Inc	***25***	100,00 / 100,00	100,00 / 100,00	100,00 / 100,00
BEST SETTING		RBF – 5 neurons – 2 attributes		

TABLE XI. HIT PERCENTAGE OF NEURAL NETWORKS TO ESTIMATION OF CARBON DIOXIDE.

Training Algorithm	Number Neurons Hidden Layer	Correct Diagnosis (%) 2 attributes / 3 attributes		
		Training	Validation	Test
LM	***5***	100,00 / 100,00	100,00 / 100,00	100,00 / 100,00
RBF-Inc	***5***	100,00 / 100,00	100,00 / 100,00	100,00 / 100,00
LM	***15***	100,00 / 100,00	100,00 / 98,33	98,04 / 100,00
RBF-Inc	***15***	100,00 / 100,00	100,00 / 100,00	100,00 / 100,00
LM	***25***	100,00 / 100,00	100,00 / 98,33	98,04 / 96,08
RBF-Inc	***25***	100,00 / 100,00	100,00 / 100,00	100,00 / 100,00
BEST SETTING		MLP-LM – 5 neurons – 2 attributes		

TABLE XII. HIT PERCENTAGE OF NEURAL NETWORKS TO ESTIMATION OF METHANE.

Training Algorithm	Number Neurons Hidden Layer	Correct Diagnosis (%) 2 attributes / 3 attributes		
		Training	Validation	Test
LM	***5***	97,86 / 94,29	96,67 / 96,67	100,00 / 94,12
RBF-Inc	***5***	97,86 / 97,86	96,67 / 96,67	100,00 / 98,04
LM	***15***	97,86 / 92,14	96,67 / 96,67	100,00 / 90,20
RBF-Inc	***15***	97,86 / 97,86	96,67 / 96,67	100,00 / 100,00
LM	***25***	97,86 / 97,86	96,67 / 96,67	96,08 / 96,08
RBF-Inc	***25***	97,86 / 97,86	96,67 / 96,67	100,00 / 100,00
BEST SETTING		MLP-LM – 5 neurons – 2 attributes		

TABLE XIII. HIT PERCENTAGE OF NEURAL NETWORKS TO ESTIMATION OF ETHYLENE.

Training Algorithm	Number Neurons Hidden Layer	Correct Diagnosis (%) 2 attributes / 3 attributes		
		Training	Validation	Test
LM	***5***	86,43 / 86,43	96,67 / 96,67	78,43 / 78,43
RBF-Inc	***5***	86,43 / 82,14	96,67 / 93,33	82,35 / 74,51
LM	***15***	86,43 / 86,43	96,67 / 96,67	76,47 / 80,39
RBF-Inc	***15***	86,43 / 86,43	96,67 / 96,67	82,35 / 82,35
LM	***25***	86,43 / 85,71	95,00 / 95,00	76,47 / 80,39
RBF-Inc	***25***	86,43 / 86,43	96,67 / 96,67	82,35 / 82,35
BEST SETTING		MLP-LM – 5 neurons – 2 attributes		

TABLE XIV. HIT PERCENTAGE OF NEURAL NETWORKS TO ESTIMATION OF ETHANE.

Training Algorithm	Number Neurons Hidden Layer	Correct Diagnosis (%) 2 attributes / 3 attributes		
		Training	Validation	Test
LM	***5***	58,57 / 57,86	66,67 / 66,67	60,78 / 56,86
RBF-Inc	***5***	58,57 / 58,57	66,67 / 66,67	60,78 / 56,86
LM	***15***	58,57 / 55,71	66,67 / 58,33	60,78 / 43,14
RBF-Inc	***15***	58,57 / 58,57	66,67 / 66,67	60,78 / 60,78
LM	***25***	58,57 / 52,85	66,67 / 50,00	54,90 / 47,06
RBF-Inc	***25***	58,57 / 58,57	66,67 / 66,67	60,78 / 60,78
BEST SETTING		MLP-LM – 5 neurons – 2 attributes		

TABLE XV. HIT PERCENTAGE OF NEURAL NETWORKS TO ESTIMATION OF ACETYLENE.

Training Algorithm	Number Neurons Hidden Layer	Correct Diagnosis (%) 2 attributes / 3 attributes		
		Training	Validation	Test
LM	***5***	5,71 / 5,71	5,00 / 5,00	5,88 / 3,92
RBF-Inc	***5***	5,71 / 5,71	5,00 / 3,33	5,88 / 5,88
LM	***15***	5,71 / 5,71	5,00 / 5,00	3,92 / 5,88
RBF-Inc	***15***	5,71 / 5,71	5,00 / 5,00	5,88 / 5,88
LM	***25***	4,28 / 5,71	3,33 / 3,33	3,92 / 3,92
RBF-Inc	***25***	5,71 / 5,71	5,00 / 5,00	5,88 / 5,88
BEST SETTING		MLP-LM – 5 neurons – 2 attributes		

B. Thermal Fault Diagnosis

The results obtained from dissolved gases presents a high efficiency in estimation of hydrogen, monoxide and carbon dioxide and methane. Hydrogen and methane appear dissolved in oil when happen thermal failures which overheat the oil and, the carbon oxides happen because of failures which involve the cellulose.

Using this information it is possible implements a Neural Network for thermal fault diagnosis. This Neural Network makes the classification between normal samples and thermal fault samples based on the physical-chemical tests as it is showed in section V, subsection A. Thus, the chromatographs and physical-chemical characteristics relation is proved.

The table XVI presents the best ANN configuration and the table XVII their correct diagnosis percentage.

TABLE XVI. ARTIFICIAL NEURAL NETWORK SETTINGS.

ANN Settings	
ANN	MLP
Training Function	Levenberg-Marquardt
Hidden Neurons	2
Hidden Layer Transfer Function	Hyperbolic tangent sigmoid
Output Layer Transfer Function	Linear

TABLE XVII. HIT PERCENTAGE OF NEURAL NETWORKS TO THERMAL DIAGNOSIS.

Set	Minimum (%)	Mean (%)	Maximum (%)
Training	70,00	78,43	84,29
Test	58,33	73,33	91,67

VI. CONCLUSIONS

In this paper were proposed and tested two structures of Neural Networks aiming at estimation of dissolved gases from physical-chemical measures of transformers insulating oil.

The algorithm of exhaustive search presented positive results allowing the identification of most influential parameters of physical-chemical tests in a condition of dissolved gases in oil. The major part of estimations presented satisfactory results with just two physical-chemical characteristics as input of the Neural Network. This optimizes the network project, simplifying the computational efforts, and making the performance better, because it avoids the learning of details coming from the non important inputs. In terms of Neural network structure complexity, it is concluded that MLP Networks with only one hidden layer formed by 5 neurons takes the less complexity to the estimation task of dissolved gases in oil and it does not compromise the task efficiency.

It is obvious the high efficiency in estimation of hydrogen, monoxide and carbon dioxide and methane since in the major part of chromatography datas, which present physical-chemical contemporary analyze, diagnose thermal failures in the transformer showed.

By the same idea, it is explained the low quality of the estimation of the heaviest gases, as ethane and acetylene, which are dissolved in oil through electrics failures.

It is necessary emphasize that the results demonstrate the existence of the relationship between physical-chemical and chromatography measures. This relation can deepen of its studies in a way to promote a higher knowledge of the dynamics which involve the internal failures of the transformer and the dielectric qualities of the insulating oil. It appears the possibility of setting preventive criteria about degradation of oil and incipient failures in transformers.

From implementations presented, it can be concluded that it is possible to go with the evolution of dissolved gases without carrying out a complete chromatography, which in many cases is one convenient facility, because of the easy availability of physical-chemical tests.

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