Application of an Artificial Neural Network in the Use of Physicochemical Properties as a Low Cost Proxy of Power Transformers DGA Data

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ABSTRACT

This paper is about the relationship between dissolved gases and the quality of the insulating mineral oil used in power transformers. Artificial Neural Networks are used to approach operational conditions assessment issue of the insulating oil in power transformers, which is characterized by a non-linear dynamic behavior. The operation conditions and integrity of a power transformer can be inferred by analysis of physicochemical and chromatographic (DGA – Dissolved Gas Analysis) profiles of the isolating oil, which allow establishing procedures for operating and maintaining the equipment. However, while the costs of physicochemical tests are less expensive, the chromatographic analysis is more informative and reliable. This work presents a method that can be used to extract chromatographic information using physicochemical analysis through Artificial Neural Networks. It´s believed that, the power utilities could improve reliability in the prediction of incipient failures at a lower cost with this method. The results show this strategy might be promising. The purpose of this work is the direct implementation of the diagnosis of incipient faults through the use of physicochemical properties without the need to make an oil chromatography.

Index Terms — **Dielectric measurements, oil insulation, power transformers, neural networks.**

1 INTRODUCTION

POWER transformers are devices, technically and economically, essential in a transmission and distribution electric plant. It is essential to ensure its continuous operation and prevent possible failures that may occur because of their natural life cycle or electrical arrangement that are submitted [1-5].

For technical reasons associated with the natural aging of the equipment installed in an electrical system comes the need to increase performance and reliability in inferior conditions at the time of start-up, and establishing higher levels of quality and technical service. This requires an environment that resembles the real conditions of operation of this type of equipment. The operating conditions and integrity of a power transformer can be drawn from the analysis of its insulating oil. It is known that a set of analysis defined by technical standards provides diagnosis for probable fault conditions of the transformer [6, 7].

The insulating oil is widely used in electrical equipment performing, essentially, the role of an insulating and cooling medium. The electric insulation prevents the formation of the voltaic arc and promotes its extinction, while the generation of convective currents provides an effective process to remove the heat produced inside the equipment to the external environment.

The most widely studied diagnostic methods that are used to identify incipient faults in power transformers are: i) physicochemical evaluation, which determines the oil integrity; ii) chromatographic analysis that checks possible equipment failure. From these two types of analysis were defined standards and procedures for operation and maintenance of oil insulated equipment [1, 8, 9, 10, 11].

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The dielectric quality of the transformer insulating oil, and the incipient failures of thermal and electrical type of this equipment, can be determined from physicochemical and chromatograph tests [6, 7, 10, 12]. These tests are important to keep the integrity of the transformers. In the meantime, while the costs of the physicochemical tests are lower and simpler, the chromatograph one is more informative [1, 2, 13]. There are, in the technical literature, papers that point to the correlation between these two types of tests [1, 10, 14, 15].

The uses of these tests are the basis for developing a good maintenance plan with capability to anticipate failures while these are still incipient. Although there are a considerable number of development tools for monitoring and diagnosing the condition of power transformers, this issues presents continuous challenges [1, 15, 16, 17].

Added to this, when temperature and load are monitored it is possible an integrated view of the efforts to which the power transformer is submitted. According some authors, with these integrations is possible to use strategies to predict lifetime and operations planning [18 19, 20, 21].

However, it is a fact that a direct temperature monitoring of the transformers windings is commonly a costly intrusive process. In many cases, it is necessary to shutdown the equipment and therefore interrupting the power service. On the other hand, the use of DGA – Dissolved Gas Analysis to evaluate the current transformer conditions is a non-intrusive method and technically more cheap. The oil sample used in DGA could be taken without power service interruption.

It is noteworthy that the average lifetime of such equipment ranges from 30 to 40 years. It is therefore essential the use of maintenance techniques that protect such important and high value investment.

The methods of diagnosis based on DGA are the most studied and most applied to power transformers immersed in oil. These methods are based on the analysis of the concentration and rate of gases production generated and dissolved in transformer oil, and associates the kind of failure with the presence of these gases. For example, electrical discharges lead to the generation of acetylene while the presence of carbon dioxide is associated with overheating of the cellulose. Conventional methods of DGA have been employed for over thirty years as a successful technique that, coupled with recent technologies, gains new momentum every year. The use of these methods for followed decades led to a deep knowledge base to characterize the balance of gases inside the transformers. It is observed that the level and period of formation of gases depends not only on the age of the transformers but also of the location, nature and severity of failures that are submitted [1, 6, 7, 15, 16, 17].

This article aims to develop a methodology to explore the co-relation between the concentrations of dissolved gases in insulating oil (normally obtained by chromatograph test) and the physicochemical characteristics of the oil sample. This proposed method brings economic reduction in the information extractions relevant to foresee incipient failures of transformers. Taking advantage of the consolidated knowledge base that grew historically around DGA analyses, including several industrial standards. The ability to predict gases concentrations based on much cheaper physicochemical methods allows the use of the established DGA standards to infer transformer operating conditions [1, 2, 6, 7, 23, 25].

The relation between the physicochemical measures and the gases concentration is set in this paper through Artificial Neural Networks (ANN) which, by examples, learns how to build linear or non-linear mappings, considered universal approximators. Artificial Neural Networks (ANN) has been successfully employed in modeling and system identification of complex nature [1, 2]. Techniques that involve the application of different architectures of ANN (Multi-Layer Perceptron, Radial-Basis Function, Self-Organizing Maps, among others) have been proposed successfully for the detection of incipient faults in power transformers [1, 22, 23, 24].

2 ANALYSIS OF INSULATING OIL

The gas formation in a liquid insulation cannot be prevented, even with the most effective chemical additives. The oil and cellulose oxidation and cracking is an unavoidable spontaneous natural process inside an operational power transformer, due to the simple fact that its internal temperature rises when turned on. Most transformers are cooled by plain fins external structures, and some may reach about 200°C in a sunny day, which is quite hot. There is no way to fully stabilize oil molecules or cellulose fiber at this situation and the subsequent reducing chain reactions will take place no matter what.

Some researches look for associating the abnormal dielectrics characteristics of the oil to the occurrence of internal failures [1, 10, 14, 15]. 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 [3, 4, 5, 8, 14].

Regarding the most regularly used tests for insulating oil, there is emphasis on the DGA and the physicochemical properties. DGA provides the discovery of internal failures still in early stage. This information allows taking measures in order to attenuate the cause or even the replacement of the unit in the imminence of failure, in order to prevent the effectiveness of fault. The analysis of the physicochemical features yields data to assess the oil. The evaluation report extracted from the reference standards can categorize the analyzed oil, which may require the immediate oil replacement in case of deteriorated properties.

Despite the importance of information from these two tests and the applicability of functional relation between them, such relationships are not well defined in literature.

However, some studies mention the influence of dielectric oil in the abnormal appearance of internal faults. Such abnormalities may be related to the presence of free radicals and dissolved oxygen under the catalytic effect of copper, known as trigger for the degradation process of oil under aging [14].

Some studies show that, as the operating time of insulating oil increases, the rate of failure occurrence raises significantly [15].

Tests with spectroscopy dielectric methods present co-relation between the aging of oil and the loss factor (tan δ). Samples with degraded physicochemical properties were shown to have a loss factor dependent on temperature, according to the Figure 1 [10].

Studies of [25], demonstrate that the oil conductivity maintain ascendant relation with the temperature. Conductivity is a complementary parameter to Breakdown Voltage.

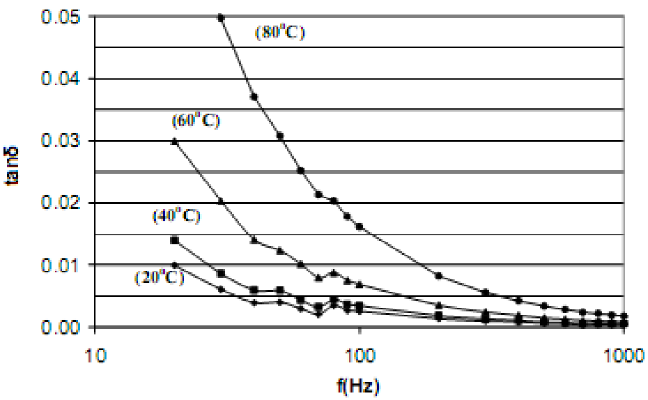

Figure 1. Spectroscopy dielectric of aged insulating oil [8].

It is known that the mechanism of gases formation inside transformers follows a thermodynamic model that associates the reaction rate of gases formation to the temperature near the failure spot [6, 7].

For the very specific case of a power transformer, there is no source of high frequency light, such as ultraviolet or other ionizing radiation, which possibly could catalyze the production of free radicals. Therefore, provided that no one have installed the transformer nearby an x- or cosmic ray source, which is the real life situation, the dominant process for oil degradation in actually oil cracking. Eventually, some electric arc formation by isolation faults takes place, however the thermal degradation is the long-term mechanism always present when the equipment is in operation. Not only the oil suffers from thermal degradation, but also the cellulose does. Due to the importance of this oil /cellulose cracking and oxidation thermal process, there are so many studies regarding it in specialized literature [26-31]

Despite the lack of application, physicochemical and chromatographic tests are run for decades, and consequently, there is a broad amount of reliable data on the characteristics of insulating oil.

The most remarkable feature of an ANN is learning by example. The application of methods based on computational intelligence, like ANN, can provide satisfactory results concerning to insulation behavior of the transformer liquid [1]. Certainly, it is quite hard to forecast by direct human rationale the link between oil degradation products and the operating condition of a transformer. However, an artificial neural network (ANN) is a proven technique with advanced capabilities of pattern recognition. This is a fact, and if such hidden patterns exist, they could possibly be revealed by the ANN.

The data in question are composed of contemporary samples of physicochemical and chromatographic analysis courtesy of a company generating electricity added to the data held by the Department of Electrical Engineering, Federal University of Ceará in a total of 357 samples. These samples are related to power transformers used at voltages between 230kV and 500kV, with manufacture date between 1961 and 2008, with start-up date ranging between 1967 and 2009. The data analyses used in the experiments have contemporary collection date between 1982 and 2009.

3 ESTIMATION OF DISSOLVED GASES USING ONE ARTIFICIAL NEURAL NETWORK

The results presented in [10] pointed clearly the physicochemical properties, which have noticeable influence in the quality of insulating oil.

The Multi-Layer Perceptron (MLP) is generally considered the most powerful and universally applicable type of ANN. In the Figure 2 is shown a MLP-ANN with one hidden layer, input and output layers. There are n neurons (x_1, ..., x_n) in the input layer, h hidden neurons h (z_1, ..., z_h), and m neurons in the output layer (y_1, ..., y_m); w_{ij} is the weight of the connection between a neuron x_i of the input layer and one neuron z_j, and β_{jk} the weight of the connection between the neuron z_j and the neuron y_k. In this network are considered too, τ_j as the value of the bias for the neuron z_j of the hidden layer, and φ_k as the bias for the output neuron y_k.

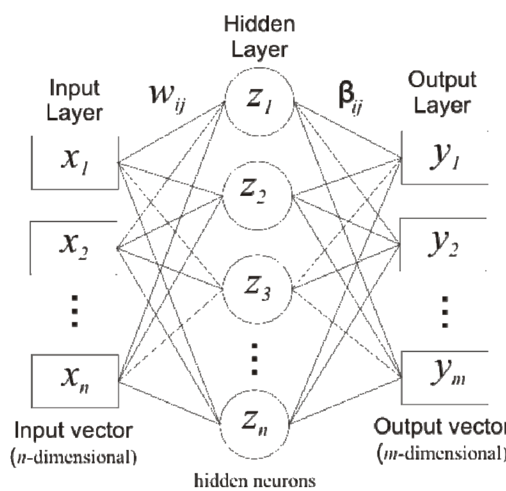

Figure 2. The Multi-Layer Perceptron ANN.

The input vector applied to the ANN is formed by the following components:

1- Acidity,
2- Breakdown Voltage,
3- Water content,
4- Interfacial tension,
5- Density,
6- Oil power factor.

The estimation of the concentration of dissolved gases is obtained as the output of the neural network. The estimated gases concentrations can be taken as an indicator to infer the possibility of incipient failures in transformers [1, 2, 7, 9, 10, 13, 24]. Thus, the concentrations of the followed gases were estimated:

1- Hydrogen (H_2),
2- Carbon Monoxide (CO),
3- Carbon Dioxide (CO_2),
4- Methane (CH_4),
5- Ethane (C_2H_6),
6- Ethylene (C_2H_4),
7- Acetylene (C_2H_2).

It was conceived a distinct ANN to each gas to be estimated with just one neuron of output. Therefore, the seven neural networks give the associative link between the input physicochemical measures and the concentration of dissolved gases in oil.

The present work relies on a comprehensive base of about 357 DGA chromatographic data sets, which was used in the development of correlations between the input and output variables, through the design of 7 different ANN-MLP. For the training process were used 60% of the data. For validate and test were separated 20% for each step, respectively. Data were normalized to encompass the minimum and maximum values in the range [-1, 1]. The training was designed with the method of Levemberg-Marquardt. The hidden neurons layer was set to 10 neurons. For statistical effect, all the ANN were trained and tested in sets of 30 repetitions.

As described in [6] and [7], measurements of dissolved gases in laboratories always provide some degree of imprecision. This imprecision alters the gas measures affecting the process of fault diagnosis.

In [32] are cited researches about 25 laboratories with expertise in 15 different countries, representing the current practices around the world in order to quantify the imprecision of measurements. The average precision of the laboratories in the referred research for all gases is within ± 15% ± 30%. Based on this, it seems reasonable to consider a quantization window of tolerance for ANN output around these values of inaccuracy of the laboratories.

At this point, it should be noted that the values of laboratory tests are expressed in parts of the gas per million parts of oil (p.p.m.) volumetrically and are based on a large power transformer, with several thousand gallons of oil. With a smaller volume of oil, the volume of the formed gas will result in a greater variation in the gas concentration.

The diagnostic results based on inaccurate laboratory values can be misleading in some cases. When it is not possible deal with the random variability of the DGA data and its consequent ambiguity of the results of the diagnostic, the default values of accuracy based on international surveys can be used, like present in [32].

The results are presented in Tables 1 to 7 through the hit rate in the training and testing for each ANN dissolved gas estimator. Where hit rate is the comparative the value between the gas from the chromatography and the value estimated by the neural network, i.e. how close to the actual value is the prediction given by the neural network. The measures of minimum, maximum, average and standard deviation make possible evaluating the robustness of the estimates developed by neural networks.

Table 1. Hit Percentage of Neural Networks to Estimation of Acetylene.

Hit Rate Acetylene	Training (%)	Test (%)
Minimum	93.95	91.55
Main	96.61	96.48
Maximum	99.07	100.00
Standard Deviation	1.52	2.42

Table 2. Hit Percentage of Neural Networks to Estimation of Hydrogen.

Hit Rate Hydrogen	**Training (%)**	**Test (%)**
Minimum	97.21	94.37
Main	97.86	87.65
Maximum	98.14	100.00
Standard Deviation	0.54	2.93

Table 3. Hit Percentage of Neural Networks to Estimation of Ethane.

Hit Rate Ethane	Training (%)	Test (%)
Minimum	92.09	80.28
Main	95.19	89.01
Maximum	98.14	98.59
Standard Deviation	1.65	4.44

Table 4. Hit Percentage of Neural Networks to Estimation of Ethylene.

Hit Rate Ethylene	Training (%)	Test (%)
Minimum	86.51	78.87
Main	89.74	84.41
Maximum	93.95	92.96
Standard Deviation	1.81	3.77

Table 5. Hit Percentage of Neural Networks to Estimation of Methane.

Hit Rate Methane	Training (%)	Test (%)
Minimum	88.37	76.06
Main	91.00	85.02
Maximum	93.95	92.96
Standard Deviation	1.56	4.23

Table 6. Hit Percentage of Neural Networks to Estimation of Carbon Dioxide.

Hit Rate Carbon Dioxide	Training (%)	Test (%)
Minimum	82.58	63.79
Main	85.28	73.97
Maximum	88.76	84.48
Standard Deviation	1.90	5.98

Table 7. Hit Percentage of Neural Networks to estimation of Carbon Monoxide.

Hit Rate Carbon Monoxide	Training (%)	Test (%)
Minimum	91.11	55.93
Main	95.22	67.34
Maximum	99.44	79.66
Standard Deviation	1.93	5.75

4 DISSOLVED GAS INFLUENCE IN PHYSICOCHEMICAL PROPERTIES

After training the ANN, it was used to obtain graphically the relation between the physicochemical properties and the dissolved gases concentrations Figures 3 to 9.

For the construction of graphs displayed, using the neural networks developed, it was necessary to use considerations of ideals, because neural networks were designed with multiple inputs and one output. Thus, the entry of interest was varied within the universe of study while other inputs were kept within its limits considered normal.

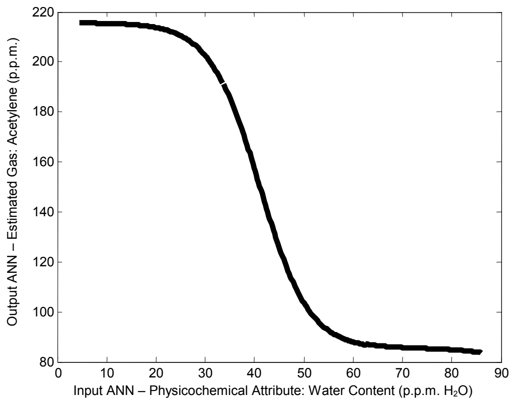

Figure 3. Input x Output - ANN: Water Content *x* Acetylene.

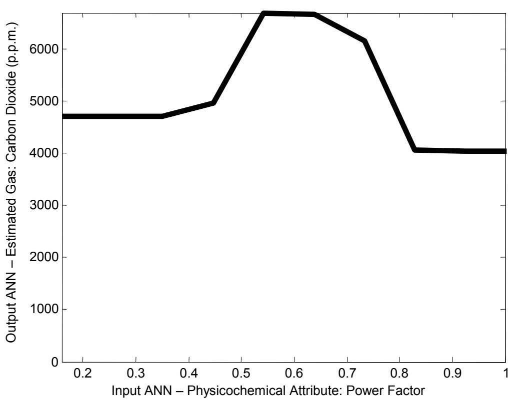

Figure 4. Input x Output - ANN: Power Factor *x* Carbon Dioxide.

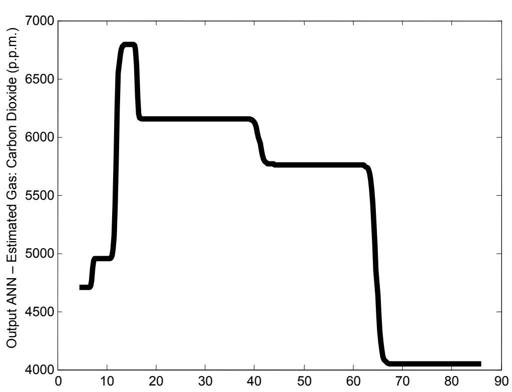

Figure 5. Input x Output - ANN: Water Content *x* Carbon Dioxide.

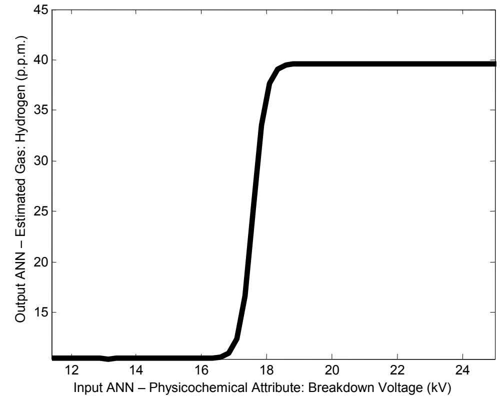

Figure 6. Input x Output - ANN: Breakdown Voltage *x* Hydrogen.

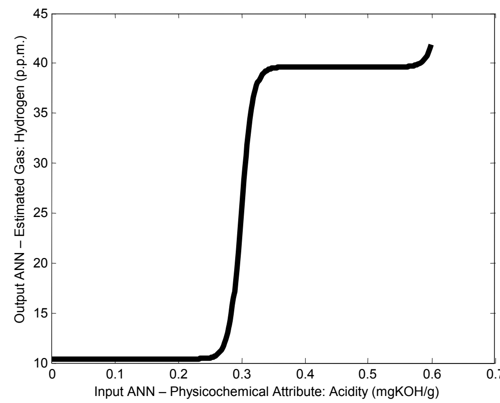

Figure 7. Input x Output – ANN: Acidity *x* Hydrogen.

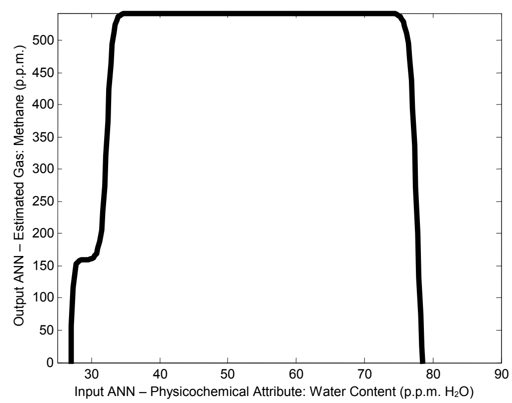

Figure 8. Input x Output - ANN: Water Content *x* Methane.

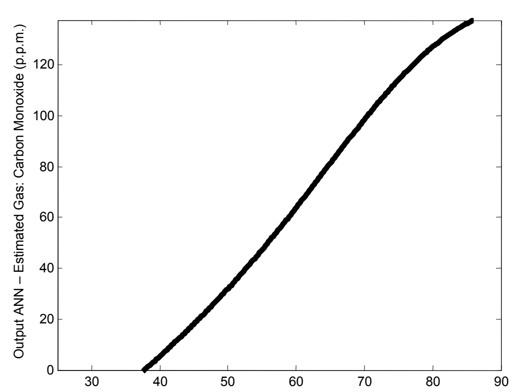

Figure 9. Input x Output – ANN: Water Content *x* Carbon Monoxide.

It is observed the remarkable variation of characteristic of Water Content when there is generation of Carbon Monoxide, Carbon Dioxide, Methane and Acetylene, according to Figure 9, Figure 5 and Figure 8, respectively. The first three refers to failures in low temperature or under condition of overheating in cellulose.

Methane, according to [6] and [7], can be generated from a soft overheat on high temperatures coming from more severe failures. Therefore, the attribute value Water Content proves to be a good indication of decrease in insulating oil quality and, as a result, in probability presence of incipient failures in transformer.

Regarded to Monoxide and Dioxide Carbon, in a circumstance where the cellulose is submitted to an extreme high temperature, as electric arcs, the generation of carbon monoxide (CO) gets raised very fast in comparison to the production of carbon dioxide (CO_2). But, in a situation of little overload or ventilation restrictions, where significant heat generation takes place, the CO_2 increases more quickly than CO, therefore the rate of CO/CO_2 presents the values from 1:20 to 1:10. This justifies the appearance of curves being opposite in Figures 9 and 5 in relation to Water Content.

The relation of Water Content in oil with acetylene, which is generated from high temperatures of more severe failures, confirms the tendency presented previously. As observed in Figure 3, high concentration of acetylene are found when one has low values of Water Content, confirming that presence of high values for Water Content there is low tendency of electrical conduction [25].

Thus it is concluded that as the temperatures of failures get higher, there is less presence of Water Content in oil.

In [1, 10, 25], there are references to oils in adequate conditions of use with high capacity of insulating and very low Power Factor values, independent on temperature in operation frequencies. Oils in precarious conditions present thermal instability, marked with high losses, or high Power Factor values, beyond of dependency on temperature. For the same reason, Figure 4 demonstrates that the production of Carbon Dioxide stays in high rates for values of losses between 0 and 1.

The model for formation of gas dissolved in oil in relation to temperature demonstrates that there is formation of Hydrogen even in low temperatures, but in smaller quantity than the Methane [6, 7]. In a possible increase of temperature before a failure, there is inversion in the relation between Hydrogen and Methane production. This relation can serve to identify failures of low temperature. This information can be verified in Figure 6, where there is little variation in Hydrogen production for Breakdown Voltage variation. A large variation in Hydrogen production may indicate a favorable environment to electric failures resulting from electric arc, because of Breakdown Voltage low value.

In the oil degradation process, by catalytic action of metals, like copper, are formed hydrogen peroxide, which are unstable products and can liberate oxygen resulting in further oil oxidation. Later, acids are formed and other polar products that are chemically actives. In this phase there is Acidity increase and the oil Power Factor increases as well. The increase of the Power Factor generates, consequently, thermal instability. With the Acidity increase occur a decrease of Interfacial Tension and an increase of capacity of water dissolution, according to Figure 7. A possible raise of dissolved water quantity may have influence in Breakdown Voltage and turn the transformer more failure prone.

5 DIAGNOSIS OF INCIPIENT FAILURES FROM PHYSICOCHEMICAL PROPERTIES

The diagnosis of incipient failures is made using data from chromatography of insulating oil. The physicochemical properties are used in parallel only to certify the quality of oil in its function as an insulator and coolant. The purpose of this work is the direct implementation of the diagnosis of incipient faults through the use of physicochemical properties without the need to make an oil chromatography. Thus, a sole analysis would provide the two diagnoses, about failures and oil quality, a fact that brings clear benefits to the logistics of maintaining large power transformers. The diagram shown in Figure 10 illustrates the aim of this paper.

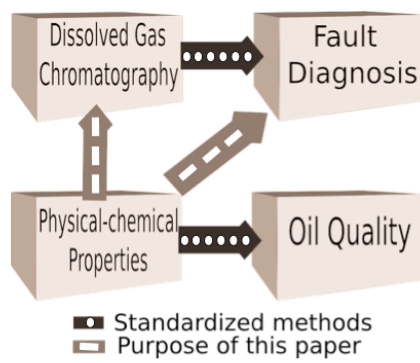

Figure 10. Aim of the paper.

The chromatographic and physicochemical analyses, contemporary, were taken from a series of transformers of a generation company of power to fulfillment of training stages, validation and tests of developed ANN. In order to provide fault diagnosis two ANN models were designed. A Multi-layer Perceptrons (MLP) with Levemberg-Marquardt training, the same model used in section 3. Another model designed to classify was training with Adaptive Back-Propagation [1, 15, 17]. From obtained samples in Section 3, a number of 135 were used in diagnostic of incipient failures in their reports, improving the test of diagnostic of incipient failures starting from physicochemical characteristics. This sample's universe presents 44 normal classification, 30 thermal faults, 72 electrical faults. It is important to note that the inclusion of samples in normal conditions enables the neural network to classify transformers without faults. The number of samples with faults ensures the diversity of cases robust neural network training. This approach yields a higher rate prediction.

With respect to the ANN design, the sets available for training and tests comprise 94 and 41 samples, respectively. The wanted output is diagnostic provided in the technical report of the specialist responsible for analyses of insulating oil based on IEEE/IEC methods [6, 7].

For the training process were used 70% of the data. For test were separated 30%. From the data mean and standard deviation, the data are normalized with mean equal to 0 and variance 1. The hidden neurons were set to 2 layers. For statistical effect, all the ANN were trained and tested in sets of 20 repetitions. The Table 8 presents the ANN's configurations.

The Table 9 presents the values of the rate hit for MLP trained by the algorithm Levenberg-Marquardt (identified by LM) and the Adaptive Back-Propagation (identified by ABP) in sets of training and test data (minimum, mean, maximum and standard deviation).

Table 8. ANN's Configurations.

MLP-LM Configuration	
Training Function	Levemberg-Marquadt
Hidden Neurons	20 - 20
Output Neurons	3
Hidden Layer Transfer Function	Hyperbolic tangent sigmoid
Output Layer Transfer Function	Linear
MLP-ABP Configuration	
Training Function	Adaptive Gradient Descent
Hidden Neurons	7 - 10
Output Neurons	3
Hidden Layer Transfer Function	Hyperbolic tangent sigmoid
Output Layer Transfer Function	Linear

Table 9. Results of the Diagnosis of Incipient Faults - Physicochemical Properties.

ANN	Training (%)				Test (%)			
	Min	Mean	Max	Std	Min	Mean	Max	Std
MLP-LM	94.29	96.51	98.86	1.19	67.11	72.24	84.21	4.94
MLP-ABP	95.74	96.81	98.94	1.09	65.85	71.71	78.05	3.39

Due to the unprecedented use of data from physicochemical tests for obtaining Fault Diagnosis in Transformers, was decided to propose a comparison of this with the traditional methods. The intent of this comparison is to provide a qualitative analysis of the use of physicochemical directly into the fault diagnosis.

As a comparative form, the Table 10 presents the application of IEC - International Electrotechnical Commission and IEEE - Institute of Electrical and Electronics Engineers methods in the data used to elaborate the ANN. These standards include the use of methods: Key Gas, Dörnenburg and Rogers Ratio [6, 7]. The hit rate is calculated in comparison with the technical report of the specialist. In data series, some cases are in an area of no-decision of standards, where it is not possible to do any diagnostic based on rules of standard, as shown is Table 11.

Table 10. Results of the Diagnosis of Incipient Faults – IEEE/IEC Methods.

	Hit (%)	No-decision cases
Key Gas	45.19	0
Rogers Ratio	40.00	26
Dörnenburg	43.70	79

Table 11. Samples of Chromatography Data

Samples	1	2	3	4	5
H_2	15	32	479	75	29
CH_4	0.6	26	109	89	76
CO	24	166	84	756	594
CO_2	359	2569	1433	4367	3184
C_2H_4	0	80	133	10	63
C_2H_6	0	12	11	68	28
C_2H_2	0	0.6	1121	0	0
Key Gas	Normal	Thermal	Electrical	Thermal	Thermal
Rogers	Normal	No-decision	Electrical	No-decision	Thermal
Dörnenburg	Normal	Normal	Electrical	No-decision	Thermal

6 CONCLUSIONS

In this paper is proposed a method to estimate the dissolved gases from the physicochemical analyses of transformers insulating oil.

The association between the physicochemical oil properties and gas chromatography was confirmed by testing the proposed ANN structures. Through the use of ANN can be verified the variation of some physicochemical properties as a function of dissolved gases in oil. According to comments pointed out in Section 3 can be observed the compatibility between the theories of gases formation inside the power transformer with respect to the results estimated by ANN.

From the presented implementations, it can be concluded that it is possible to follow the evolution of dissolved gases without performing a complete chromatography, which in many cases is a convenient facility, due to easy availability of companies' physicochemical tests. Especially in the time interval between the chromatography tests. Because, according to the standard, this can be up to 12 months. During this time, it is important to have a way to evaluate the incipient faults.

The proposed method requires further developments to come forward with more efficiency compared to traditional methods of fault diagnosis in transformers. However, it is presented the promising feature of this innovative method.

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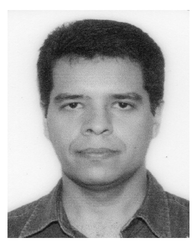

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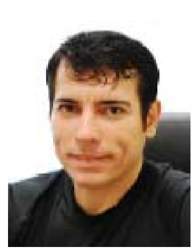

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