# ARTIFICIAL NEURAL NETWORKS FOR PREDICTING THE GASSING TENDENCY UNDER ELECTRICAL DISCHARGE IN INSULATING OIL FOR EXTENDED TIME

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**Abstract –**. *This study will focus on the investigation of the effect of electrical discharge on physical, chemical, electrical properties of transformer oil, and on the development of a mathematical model describing the gassing of insulating oil under electrical discharge, using the information contained in the measured values.*

*For predicting the gassing tendency for extensive ageing periods, we use the model developed, for an intelligent system design. The predictor's parameters are chosen based on their influence degree by the electrical field.*

*Various scenarios were considered. The study was carried on two types of fluids, under electrical stress for different ages. The 6802, 6181 and 924 ASTM tests methods were used for the measurements of parameters in degradation. All the results obtained are summarized and compared.*

*The properties which are strongly dependent have been specified, a multiple linear regression model for each fluid as a function of its DDP, DDF, turbidity and aging period is developed. This model is for the estimation of the gas quantity cumulated under electrical discharge. The prediction is made, by implanting the stepwise regression results into a neural network system, which has been tested on experimental results obtained from laboratory samples, and high prediction accuracy has been achieved.*

***Keywords***- *insulating fluids, electrical discharge, dissolved decay product, Dielectric Dissipation Factor, Stepwise Regression, Neural Network.*

## 1. Introduction

Power transformers are critical, highly loaded and expensive part of the electricity generation and distribution network. In these expensive equipments, large quantities of fluids are used, with a two-fold function: to insulate electrically and to dissipate the heat generated by the windings. [1].

In previous studies [2,3], the prediction of parameters degradation had been carried on insulating fluids in service. The behaviours of some properties had been investigated and predicted under thermal aging only. The necessity to study and predict the parameters degradation under other service condition mode has become highly important.

The decay products which darken the color of in-service-aged oil, cannot be formed without breaking the hydrocarbon chains. The ageing process is attributed to the decomposition of hydrocarbon molecules by either thermal or electric stresses and the chemical aggressiveness of dissolved oxygen [4,5]. The energy required for the decomposition of weakly bonded hydrocarbons is supplied in this case by the high voltage stress. The absorption of large amount of energy causes electronic excitation of molecules, which in certain cases leads to the haemolytic breakdown of weak chemical bonds generating gases. When this process takes place, the evolve gas leaves behind in the liquid phase the bulk of the broken molecule Since this remaining part of the decomposed hydrocarbon is a free radical, there is a high probability that it will react with a similar free radical which is no longer soluble in the blend of hydrocarbons. This is an invisible solid suspension, known under the generic name of x-waxes.[4-6]

In this contribution, investigations were performed about fluids during the electrical aging for extended period, by studying the turbidity, spectrophotometer (ASTM D6181 and D6802), and electrical parameters (ASTM 924). The experimental results obtained are used to developing stepwise regression model by selecting the most significant predictors.

The developed model was trained by neural network technique; it can predict the evolution of gas in the transformer insulating fluids in high periods.

The results used for testing the robustness of the neural network model, are obtained from experimental test in Laboratory of Research, in Insulating Liquids and Mixed Dielectrics for Electrotechnology (ISOLIME), University of Quebec at Chicoutimi, Qc, Canada [7]

## 2. Background

### 2.1 The transformer oil parameters

The insulation oil used in power transformers consists of saturated hydrocarbons as paraffin and naphthen, and can neither conduct current nor solute water. Oil conductivity depends on oil type and increases with aging by-products. Contaminants such as residues from refinery, pollution and particularly ageing/oxidation products enable the oil to conduct ionic current. Oil oxidation/degradation by products is subdivided into soluble (dissolved) products and insoluble (suspended) products. [8]

The dominating an ageing product of oil oxidation contribution is made by carbonic acids. Carbonic acid and water can dissociate to ions and hence increase conductivity considerably [8].

$$H - COOH + H_2 \rightarrow H - COO^- + H_3O^+ \qquad (1)$$

According to M. Koch et al. [9], only a combination of water and a dissociable substance will increase conductivity. Some authors found out, that water will not increase the conductivity: It increases the conductivity because of its self-dissociation, but this is hardly measurable. In a combination with a dissociable substance like acid the conductivity will increase considerably. [8]

### 2.2 Electrical stress

The free electrons are the primary source of energy for bond breakage covalent chemical (approximately 4eV ≈ 386 kJ mol-1). The free electrons injected into the liquid insulation are accelerated by the electric field. The collision of a fast electron with a hydrocarbon molecule M may be either elastic or inelastic [8]. Whereas stable molecules reaching their singlet excitation level (M*) usually release the absorbed energy as a quantum of harmless fluorescent light (hν), vulnerable molecules (R-R’) decompose and generate a pair of free radicals (R• and R’•). As their population increases, some gaseous or liquid fractions may capture a free electron and form an ion. [8]

$$R\text{-}R' + h\nu \rightarrow R\bullet + R'\bullet$$
$$R\bullet + e^- \rightarrow R^-$$

The accumulation of such ionized molecules increases the dissipation factor of the insulation. Alternatively, large free radicals may combine, leading to the formation of an insoluble colloidal suspension.

Electrical discharge produces gases, carbon and free radicals. When discharges-by-products or oxidation-by-products accumulated in the oil ducts or at oil-paper interface, heat transfer will be very poor which result in paper overheating [5, 8].

### 2.3 Artificial Neural Network (ANN)

Neural networks have been developed to be analogous with the neural system in the human body with simple units called neurons. The neurons are collecting signals from other neurons after being weighted in connection links.

The input samples in the first layer are sent to the hidden layer through weighted connection links. The hidden layer calculates its net activation as in the following equation: [10-12]

$$net_j = \sum_{i=1}^{d} x_i w_{ij} + w_{j0} \qquad (2)$$

Where d is the number of inputs features, xi is the $i^{th}$ input node, and $w_{ij}$ represents the weights between the $i^{th}$ input node and the $j^{th}$ hidden node. The output of the hidden layer, which is a nonlinear function of its net activation, is given by[11, 12]

$$y_j = f(net_j) \qquad (3)$$

The output layer calculates its net activation as follows:

$$net_k = \sum_{i=1}^{nh} y_j w_{kj} + w_{k0} \qquad (4)$$

Where $N_h$ is the number of hidden nodes and $w_{kj}$ is the weights between the $K^{th}$ input node and the $j_{th}$ hidden node.

Since gradient descent with momentum is used for neural network learning,, continuous tan sigmoid activation function to map the nonlinear correlation between the proposed inputs and outputs as defined in the following equation: [11,12]

$$\Delta w_{ij}(t) = -\eta.\delta_i.x_j + \alpha_m.\Delta w_{ij}(t-1) \quad (5)$$

η: the learning factor

The $\alpha_m.\Delta w_{ij}(t-1)$, is the momentum. $\alpha_m$ can tacking the values between 0.1 and 0.9. The adaptation of its values as well as η, give a good results [13,14]

The optimum weights are learned by minimizing the training error given in the following equation: [12]

$$E_t = \frac{1}{2}(e)^2 = \frac{1}{2}(d - y_k)^2 \quad (6)$$

Where E is the mean square error and y is the target output at the $k^{th}$ output node.

The weight values and the number of neurons in hidden layers will be maintained until reaching the highest prediction accuracy. [11-13]

ANN has proven their efficiency in different power system applications. The Multi Linear Perceptron (MLP), has been successfully used in predicting transformer insulation diagnostics parameters with high accuracy. [13, 15]

## 3. Experimental Results and discussions

### 3.1 Insulating Fluids Under Electric Discharge

The amount of gases evolved under the impact of electrical stress by a sample of fluid was accurately measurable by using the ASTM Test Method D6180 [16], which simulate conditions close to real life conditions. A Merell-based test cell type, was used (Figure 1). The free electrons were generated by a cylindrical copper electrode 15 mm in diameter and 10 mm long sealed in the center of Erlenmeyer glass, and suspended above the oil. A volume of 100 ml of oil was used. [7,16].

Before applying the voltage, the discharge cell was vacuumed down to 1 Torr (133 Pa). After the degassing, the insulated fluid specimen was subjected to high voltage discharge of 10 kV for 5h, 12h, 24h,50h and 75h.

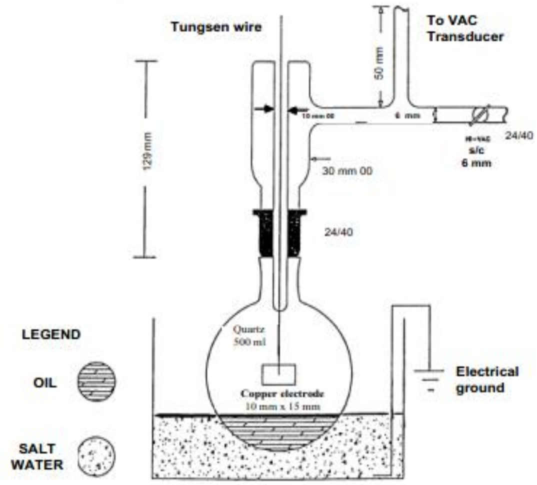


Fig.1. Discharge cell according to ASTM D6180 [16]

The increased pressure inside the discharge cell was recorded to assess the amount of evolved gasses.[7,16]. The results was reported in figure 2

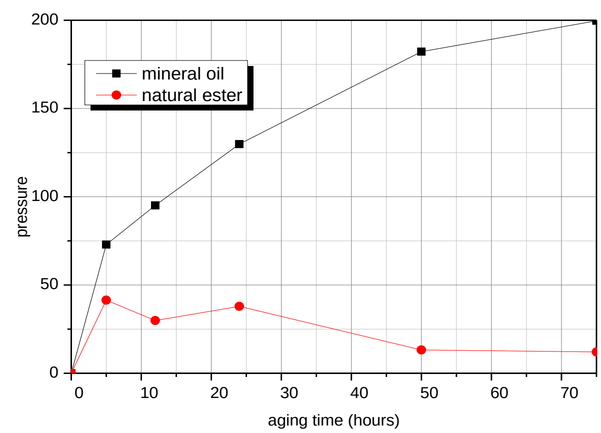


Fig.2. Fluids samples gassing diagram

Obviously, the gassing tendency of natural esters is much lower than that of mineral oils. This is well-known fact as emphasized by German and Fuoss [2,3]. According to these authors, vegetable fluids are generally better than mineral oils. This low gassing tendency of natural esters is most likely due to the amount of unsaturated, non-aromatic molecules as compared to mineral oils [5, 8].

### 3.2 Dissolved Decay Product

The ASTM D 6802[17] method is based upon the observation that in the range of visible spectrum, all brands of new insulating liquids are almost completely transparent to a monochromatic beam of light. On the contrary, when the fluid contains decay products, the absorbance curve, as determined by a scanning spectrophotometer, significantly shifts to longer wavelengths [5]. The numerical integration of the area below these absorbance curves permit the relative content of dissolved oxidation decay products (DDP) in the fluid samples.[5,6]. The results are reported in Figure 3 and 4.

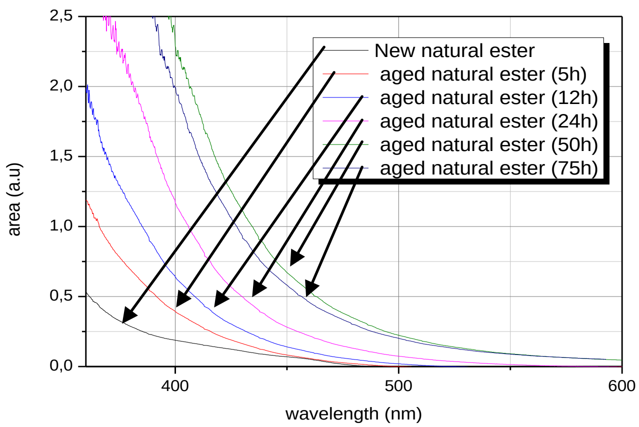


Fig.3. Absorbance curve illustrating the Dissolved Decay Products of natural ester

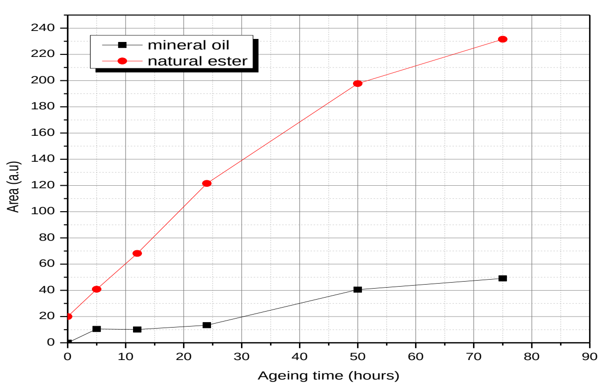


Fig.4. Dissolved Decay Products of mineral oil and natural ester after D6180 test

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### 3.3 Insoluble Decay Products

The energy of electrical field can generate not only soluble decay products that darken the color of aged oil [5], but also produce large insoluble molecules. Indeed, large free radicals may combine, leading to the formation of insoluble colloidal suspensions that affect the properties of the insulating fluid. The collision of two large free radicals leads to the formation of large colloidal compounds having a molecular weight between 500 and 600. [5,6]

The increase in turbidity under electrical discharge, proves the formation of colloidal suspensions measured by ASTM Test Method D6181[18], the results reported in figure 5, show that the turbidity goes up, in reason of the secondary chemical reaction between the hydrocarbure chains breakdown.

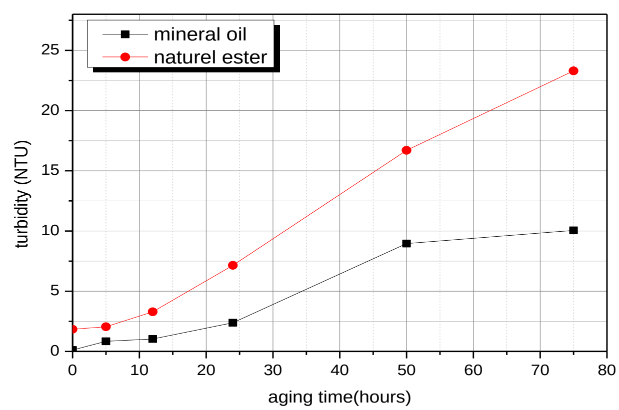


Fig.5. Turbidity of mineral oil and natural ester after D6180 test

### 3.4 Electrical properties

As the population of free radicals increases, their unpaired electrons can be coupled with a free electron to become a charge carrier that tends to increase the dissipation factor of the fluid. [5]

The measurements of the loss factor were performed with the Insulation Diagnostic Analyser IDA200 using the liquid test cell type 2903 for liquid insulation by Tettex [19]. The frequency scans of the loss factor of the two fluids samples measured at 100°C are given in Figures 06 and 07, these figures reflect the impact of electrical discharge on mineral oil and the natural ester.

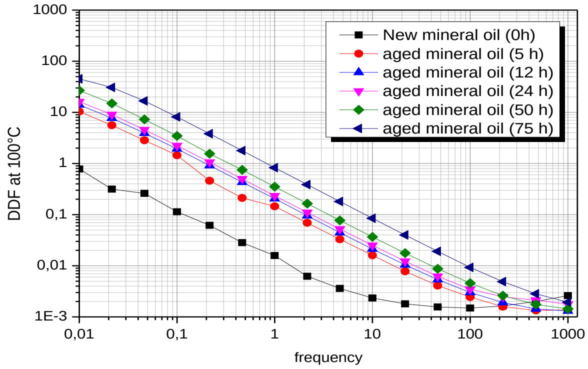


Fig.6. Frequency scans of the dissipation factor for mineral oil after 6180 test

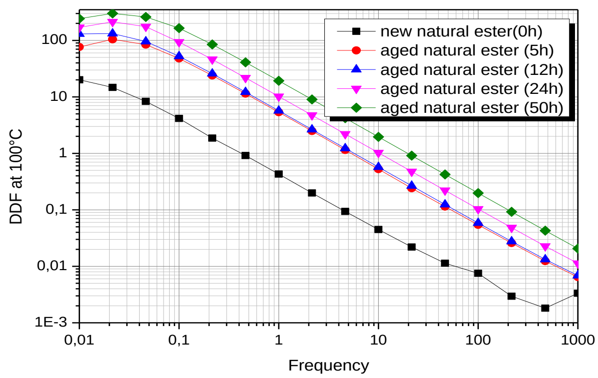


Fig.7. Frequency scans of the dissipation factor for natural ester oil after 6180 test

## 4. The Transformer fluids parameters Model

From above results, we can remark that the physical and electrical parameters of the insulating fluids effect gassing tendency under electrical stress. These results propose correlation between pressure of the gas accumulated in the discharge cellule, and the fluids parameters influenced by the gassing process. However, such correlation is complex and nonlinear.

The experimental results obtained indicate that insulating fluids gassing is strongly dependent on their DDP, Turbidity and DDF. Also there is a mutual dependence and interaction between the DDP, DDF and Turbidity. Therefore it can be concluded that a model for the gassing that incorporates the three parameters and aging period, will be comprehensive and this represents a justified conclusion from this study.

### 4.1 Modeling technique

In this section modeling of the results has been carried out as follows:

1. Modeling of the aging period dependent properties namely pressure, DDP, DDF and turbidity
2. Modeling of the gassing evolution of each fluid as a function of its three parameters and aging time.
3. Combining the results into a single equivalent model, called the general model, this later will be implanted in neural network system for gassing prediction.

A polynomial regression is proposed for modeling the gassing tendency (pressure value) as a function of its DDP, DDF, turbidity and discharge period; The least squares technique is implemented for the derivation of these models [10,14].

#### a) Modeling of parameters as function of period:

The experimental results presented in this paper, are obtained from ASTM tests in ISOLIME laboratory in Canada, this ASTM tests are :

- ASTM 6802-10, Test Method for Determination of the Relative Content of Dissolved Decay Products in mineral oil [17].
- ASTM 6181–12 Method for Measurement of Turbidity in Mineral Insulating Oil [18].
- ASTM 924–08, Test Method for Dissipation Factor (DDF) [19].

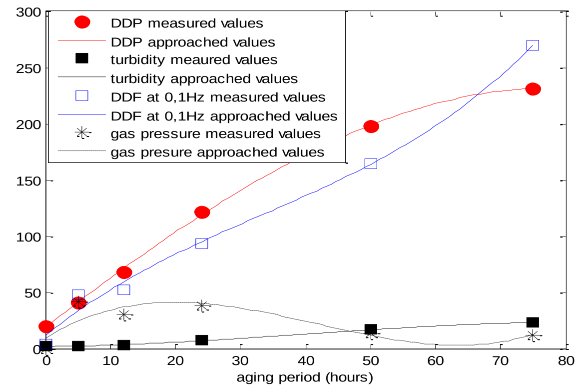


Fig.8. Modeling parameters as function of discharge period (natural ester)

The approach model for the gas pressure, DDP, Turbidity and loss factor as a function of its electrical discharge period has the following form:

$$Y(x) = A_0 + A_1 x + A_2 x^2 + A_3 x^3 + \cdots + A_n x^n \quad (7)$$

Where: Y (x ) is the dependent variable $A_0$, $A_1$… are the model constants which are required to be determined, and x is the aging period.

In figure 8, we can see that the approach model in function of time aging give a good results, there is a high approximation between the pressure measured values and the modeled ones.

### b) Modeling of gassing evolution as a function of the fluids parameters and the discharge period:

The gassing diagram can be modeled by a multiple linear regression model which has the following form:

$$F(x_1, x_2, x_3, x_4) = B_0 + B_1 x_1 + B_2 x_2 + B_3 x_3 + B_4 x_4 \quad (8)$$

Where:

$F(x_1,x_2,x_3,x_4)$ : is the pressure of gas generated under electrical discharge.

$x_1$ : is the DDP value, $x_2$ : is the turbidity, $x_3$,: the Dissipation factor at 0.1 Hz and $x_4$ is the aging time (hours).

$B_0$, $B_1$, $B_2$, $B_3$ and $B_4$ are the model constants, which can be determined by the least squares technique [12,13]. The measured and predicted values for the pressure are included in Table 1. This prediction has been carried out by two methods; the first one depends on the substitution of the measured values of the parameters at the aging period in the multiple linear regression model. This value will be given by the designation Pred. value (1)

In the second method the values of the parameters are predicted first from their individual models as a function of electrical discharge period, Eq. (8) using their corresponding constants, and then these values are substituted in the pressure multiple linear regression models. This value will be given by the designation Pred. value (2)

Table 1 shows some of the predicted and measured values of the gas pressure generated under electrical discharge. From this table we can see amelioration in the results using the second method; the predicted and measured values are in good agreement. For best seen, the results of the two methods are reported in figure 9.

Table.1. gassing prediction results

| | Mineral oil | Natural ester |
|---|---|---|
| A0 | 18.1398 | 7.1942 |
| A1 | 9.7761 | -5.0481 |
| A2 | 15.3734 | 0.6117 |
| A3 | -83.1098 | -7.1448 |
| A4 | -56.8409 | -1.0753 |
| Measured Value | **182.2** | **13.2** |
| Pred. Value (1) | **176.9630** | **12.1061** |
| A0 | 108.9386 | -8.0831 |
| A1 | 21.7637 | -4.7459 |
| A2 | -13.3247 | 0.6959 |
| A3 | -28.5974 | -4.1989 |
| A3 | -72.2839 | 1.1701 |
| Pred. Value (2) | **180.7131** | **14.0211** |

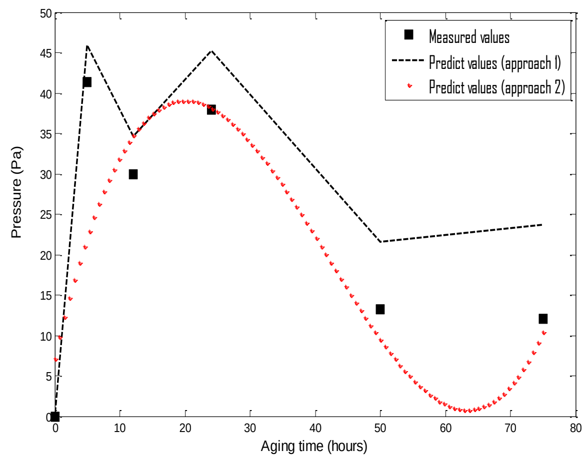


Fig.9. Model of gassing as a function of the fluids parameters and the discharge period (natural ester)

## 5. Neural network prediction

The model developed in the previous section gives good results. We adapt this model and implant it in neural network system, for predicting the evolution of gas of the insulating fluids submitting a electrical discharge, for a long period superior to 75h.. Figure 10 shows the MLP ANN architecture used for this application.

### 5.1 Learning phase:

We used LM network with one hidden layer. The input layer is made up of 4 neurons. The hidden layer contains 5 neurons, and the output layer has one neuron presenting the gas pressure. The input vector is

X=[Period, DDP, Turbidity, Loss factor at 0.1Hz] and the output vector is presented Yout= [pressure].

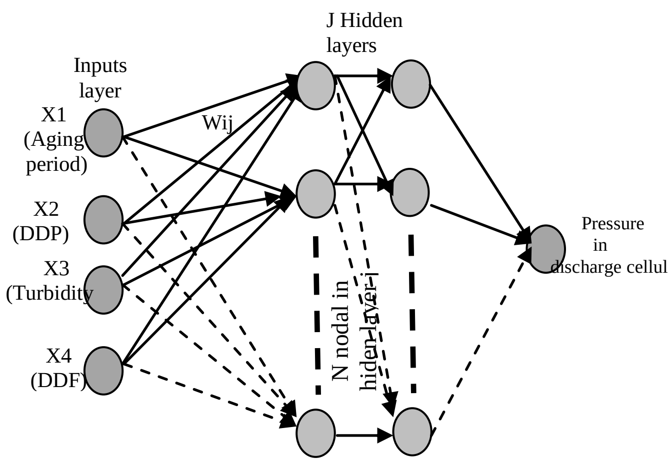


Fig.10. ANN structure used for prediction

The Levenberg-Marquardt back propagation neural network converge at 100 epoch with MSE=1.252E-5, (figure.11).

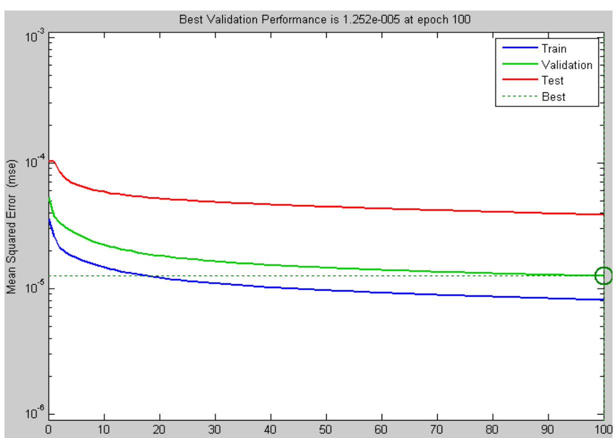


Fig.11. Error at training phase

Table 2, presents the result of neural network system designed. The error in ANN system is low than error in the model, then there is a clear amelioration in the NN system results.

Table.2. Gassing prediction by neural network

| | Mineral oil | Natural ester |
|---|---|---|
| NN Result | 180.7491 | 12.5840 |
| Experimental results | 182.2 | 13.2 |
| Error in Model | 1.4869 | 0.8211 |
| Error in NN system | 1.4509 | 0,616 |

### 5.2 Testing phase:

To test the robustness of adopted ANN system, and to predict the gassing tendency under electrical discharge for a high period: over than 75 hours, six (06) samples extracted from the experimental results in Isolime laboratory [7], will be tested by the Neural network system., we obtain the results presented in table 3

Table.3. Gassing prediction by neural network (natural ester)

| Time | DDP | Turb | DDF 0.1 Hz | Pressure NN predict values |
|---|---|---|---|---|
| 24h | 48 | 2.0000 | 60 | 41.9391 |
| 36h | 70 | 2.6000 | 75 | 43.7493 |
| 50h | 80 | 3.8500 | 81 | 40.1346 |
| 75h | 130 | 10.0000 | 115 | 20.6573 |
| 100h | 160 | 16.2500 | 135 | 28.9249 |
| 150h | 208 | 20.0000 | 150 | 34.7012 |

From the comparison between the ANN results and the experimental results of natural ester (-o-NE) showed in figure 12. We can conclude that the proposed ANN model can predict the gassing evolution for extended time, and give a good accuracy. The ANN values follow the curve presented in figure 12.

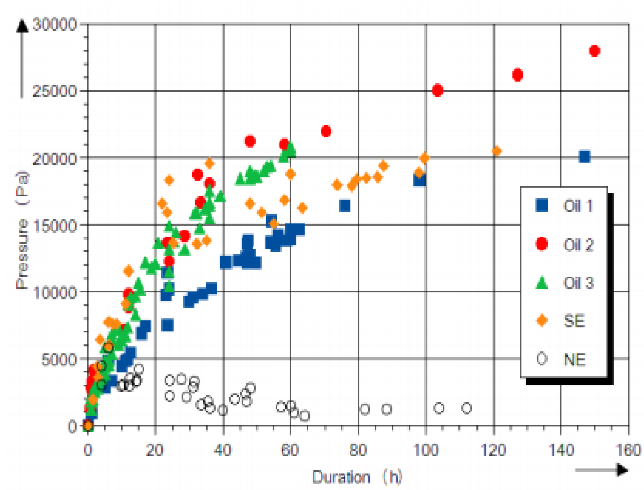


Fig.12. Insulating fluid samples gassing diagrams.[7].

## 6. Conclusion

In this contribution, a study of the stability to electrical stresses of two new insulating fluids is undertaken. The D6180 stability test and the laboratory testing procedures, developed by ASTM (D 6802, D971 and D6181) have been used to monitor degradation parameters. The results indicate that the gassing tendency of mineral oil under electrical stress follow an exponential curve and it is much lower in the natural ester than it in the mineral oil.

The dependence between the gas pressure in discharge cell and the oil properties is used for a mathematical model conception. A regression method is therefore applied, using the most significant parameters. This model has been implanted in a neural network system for two principal objectives: the verification of the results obtained from the regression model, and the prediction of the gassing for extended aging periods; the results obtained have showed a good accuracy.

As part of an overall maintenance strategy, the technique developed in this work, can be used to predict the level and severity of gas generated under electrical discharge, and can help taking restorative measures before deterioration reaches a point where failure of the transformer is inevitable

## 7. Acknowledgment

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## 8. References

1. I, Fofana, V, Wasserberg, H, Borsi and E, Gockenbach, *Challenge for Mixed Insulating Liquids for using in High Voltage Transformers. Part 1: The Dielectric Behavior of the Mixed Liquids*. In: IEEE Electrical Insulation Magazine, No. 3, 2002 pp. 18-31, Mai 2002, Vol, 18.
2. A.Bouaicha, I.Fofana: *Application de Techniques Modernes au diagnostic des transformateurs de puissance (Application of modern technique for power transformer diagnosis).* Second seminary, Master of engeneering, UQAC, Canada, 2008.
3. R. A. Ghunem, K. Assaleh and A.H. El-Hag, *Artificial Neural Networks with Stepwise Regression for Predicting Transformer Oil Furan Content*. In: IEEE, TDEI 2011.
4. J.S N'Cho, I.Fofana, A. Beroual., and J. Sabau, *The Gassing Tendency of Various Insulating Fluids under Electrical Discharge*. In: IEEE Transactions on Dielectrics and Electrical Insulation, No. 5, October 2011, Vol. 18.
5. I. Fofana, A. Bouaicha, M. Farzaneh, J. Sabau, D. Bussieres, E.B. Robertson, *Decay products in the liquid insulation of power transformers*. In: IET Electrical Power Appl., No. 3, 2010, Vol. 4, p. 177 – 184.
6. S.Boudraa, I. Fofana, and L. Mokhnache, *Influence of Various Stresses on the Physicochemical Properties of Transformer Oi. In:* Proceedings of the 18th International Symposium on High Voltage Engineering ISH 2013, August 25-30, 2013, Korea, OF3-01, p1794-1798.
7. L. Loiselle, I. Fofana, PJ. C. Olivares and E. Campero, *Influence of ageing by products on the stability of some transformer fluids*. In: Proceedings of the 7th International council on Large Electric System CIGRE2012, September 24-26, 2012, Montreal, paper 112.
8. J. S. N'Cho, L. Loiselle, I. Fofana, A. Beroual and T. Aka-Ngnui,, *Parameters Affecting the Electrical and Thermal Properties of Transformer Oils*. In Proceeding of the IEEE Annual Conference on Electrical Insulation and Dielectric Phenomena CEIDP, October 17-20, 2010, West Lafayette Indiana, USA 2010.
9. M.Koch, S. Tenbohlen, *Diagnostics of Oil-Paper-Insulations using relaxation currents*. In: Proceedings of the 14th International Symposium on High Voltage ISH 2005, August 25-29, 2005, China, paper H-45.
10. Mohamed A.A. Wahab, M.M. Hamada, A.G. Zeitoun: *Novel modeling for the prediction of aged transformer oil characteristics*, In: Elsevier Electric Power Systems Research, No. 51, 1999.
11. Y.M Yeddou: *Etude de synthèse sur les réseaux de neurones et leurs applications (Synthesis study on neural network application)*. National Polytechnic School ENP, Algeria, Jun 1998.
12. S. Boudraa, L. Mokhnache: *Neural Networks Application in Transformers oil Diagnosis*.In: 6th International Conference on Systems, Signals & Devices, 2009,Tunisia.
13. S. Boudraa, *Diagnostic des huiles de transfomateur par Analyse des gas dissous DGA (Transformer oil diagnosis using Dissolved Gases Analysis DGA)*. Memory magisterial, University of Batna, Algeria, 2005
14. Matlab Toolbox, version 7.8, 2009 The MathWorks, Inc
15. L. Mokhnache, *Application de RN dans le diagnostique et la prédiction des isolations HT (Neural Network application for the diagnostic and the prediction of high voltage isolation)*, Phd thesis, ENP January 2004, Algeria.
16. ASTM Designation 6180–05, *Standard Test Method for Stability of Insulating Oils of Petroleum Origin under Electrical Discharge*. Vol. 10.03, 2005.
17. ASTM Designation 6802-10, *Test Method for Determination of the Relative Content of Dissolved Decay Products in Mineral Insulating Oils by Spectrophotometry*. Vol. 10.03
18. ASTM Designation 6181–12 (withdraw 1012): *Standard Test Method for Measurement of Turbidity in Mineral Insulating Oil of Petroleum Origin*. Vol. 10.03.
19. ASTM Designation 924– 08, *Standard Test Method for Dissipation Factor (or Power Factor) and Relative Permittivity (Dielectric Constant) of Electrical Insulating Liquids*. Vol. 10.03, 2008.