# Analysis of Power Transformer using fuzzy expert and neural network system

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**Abstract- Power transformers being the major apparatus in a power system, thus the assessment of transformer operating condition and lifespan have obtained crucial significance in latest years. Dissolved gas analysis (DGA) is a sensitive and reliable technique for the detection of incipient fault condition within oil-immersed transformers, which provides the basis of diagnostic evaluation of equipment health.**

**The first part of this paper deals with an expert system that utilizes fuzzy logic implementation into dissolved gas in oil analysis technique. To improve the diagnosis accuracy of the conventional dissolved gas analysis (DGA) approaches, this part proposes a fuzzy system development technique based combined with neural networks (fuzzy-neural technique) to identify the incipient faults of transformers. Using the IEEE/IEC and National Standard DGA criteria as references, a preliminary framework of the fuzzy diagnosis system. In the second part, artificial neural network (ANN) based fault diagnosis is presented, which overcomes the drawbacks of the previously applied fuzzy diagnostic system that is it cannot learn directly from the data samples.**

**These expert system also consider other information of transformer such as type, voltage level, maintenance history, with or without tap changer etc.**

**Keywords-Dissolvedgasanalysis(DGA),Sensitive, Reliable, Detection, Incipient, Implementation, ANN**

## I. INTRODUCTION

Power transformers play an important role in both the transmission and distribution of electrical power and its correct functioning is essential to the operation system. In service, transformers are subject to electrical and thermal stresses, causing the degradation of the insulating materials which degradation then leading to the formation of several gases. These gases tend to stay dissolved. According to the temperature reached in the area, the product of the oil decomposition change. There is a correlation between type of the gases found and these temperatures. Thus, based on the temperature on which the oil decomposition occur andas a function of the formation of the gases for that temperature, it is assumed that faults may be present. Based on dissolved gas analysis (DGA) gases, such as hydrogen ($H_2$), methane ($CH_4$), ethane ($C_2H_6$), ethylene ($C_2H_4$), acetylene ($C_2H_2$), carbon-monoxide (CO) and carbon-dioxide ($CO_2$) can be detected and the concentrations of the gases, total concentrations of the combustible gases, the relative proportions of gases and gassing rates used to estimate the condition of the transformer and the incipient faults presented.

Hence, qualitative and quantitative determination of dissolved gases in transformer oil may be of great importance in order to assess fault condition and further operating reliability of power transformers.

In some cases, conventional fault detection methods, such as Roger's, Doernenburg's, IEC 60599 ratio methods and the National Standard (MSZ-09-00.0352) etc. fail to give diagnosis. This normally happens for those transformers which have more than one fault. In multiple fault condition, gases from different faults are mixed up resulting in confusing ratio between different gas components. Only a more sophisticated analysis method such as the Fuzzy logic method could deal with this. Fuzzy logic method can overcome the drawbacks of ratio methods which can not diagnose multi-fault and no matching codes for diagnosis because of the coding boundary and the sharp codes change, thus, it greatly enhanced diagnosing accuracy.

However, the fuzzy logic system could not learn from previous diagnosis results because the membership functions and the diagnosis rules were determined by practical experience. ANN method has been used for this purpose since the relationships between the fault types and dissolved gases can be recognized by Artificial Neural Network through a training process.

## II. DISSOLVED GAS ANALYSIS

Transformer oil is prone to undergo irreversible changes in it chemical and dielectric properties due to ageing. Factors, such as temperature, oxygen, humidity, copper electrical field and electrical discharges may accelerate the ageing process [1]. Moreover, transformer oil may act as an information carrier whose condition may be related to condition of the power transformer.

Partial discharge, arcing and overheating are the three major causes of fault related gases. The energy dissipation is less in partial discharge, medium in overheating and the highest in arcing. The main gas which is generated by the mentioned partial discharge type of fault is hydrogen (H2), beside small amount of methane (CH4), because really low energy is needed for scission the C–H bonds. More energy or higher temperature is needed for the formation of ethane (C2H6) or ethylene (C2H4) which is characteristically formed gases in the case of overheated oil. And the highest energy is needed for the formation of acetylene (C2H2) in arcs. When paper is involved in a fault the main gases which are generated carbon monoxide (CO) and carbon dioxide (CO2).

## III. DGA METHODS

Various interpretative techniques have been reported in the literature to predict development of faults, such as IEC 60599 Standard's ratio codes, IEEE Standard's Roger's and Doernenburg's ratio codes, the Key gas method, CIGRE guidelines, MSZ-09-00.0352 National Standard's ratio codes and graphical techniques such as Duval Triangle method. All these methods have been based on years of experience in fault diagnosis using DGA. None of these methods are based on mathematical formulation and interpretations are heuristic in nature and vary from utility to utility. However, in recent years more consistent methods have been developed in DGA interpretation based on large number of expert system, data and failure history of transformers [2].

### *A. Key gas method*

Decomposition of gases in oil and paper insulation of transformers caused by faults depends on temperature of faults. Various faults produce certain gases and the percent of some gases have been found to mention fault types, such as overheated oil and cellulose, corona in oil and arcing in oil.

### *B. Ratio methods*

The ratio methods are the most widely used technique. Roger's, Doernenburg's and IEC ratios are all used by utilities. Typically, three or four ratios are used for sufficient accuracy, such as the original Roger's ratio method uses four ratios (CH4/H2, C2H6/CH4, C2H2/C2H4, C2H4/C2H6) to diagnose eleven incipient fault conditions and a normal condition. This method took information from the Halstead's thermal equilibrium and Doernenburg's ratios along with information from faulted units.

### *C. MSZ-09-00.0352 National Standard's method*

Considerable differences of opinion exist for what is considered a "normal transformer" with acceptable concentrations of gases.

In this Standard four-level of criteria have been developed to determine the risks of the transformers. These criterions help to determine weather a transformer is behaving normally, especially when there is no previous dissolved gas history or the transformers have been under operation for many years. The criterion uses total concentration of all combustible gases presented in Table I for the type of Generator Step-Up (GSU) Transformers and Grid Transformers separately. The transformer is considered"Normal" when the total dissolved combustible gas (TDCG) are below or within levels and also when any individual combustible gas does not exceed specified levels presented in Table II, if not additional investigation is needed.

Table I – Condition vs. operation time of the transformer

| Condition | Concentrations of the total combustible gas | | | |
|---|---|---|---|---|
| | Type | Operation time of the transformer | | |
| | | <8 year | 8…15 year | >15 year |
| V0-Normal | Grid | <35 | <45 | <80 |
| | GSU | <50 | <65 | <1000 |
| V1-Dubious | Grid | ≥350…<45 | ≥450…<80 | ≥800…<160 |
| | GSU | ≥500…<65 | ≥650…<100 | ≥1000…<16 |
| V2-Faulty | Grid | ≥450…<80 | ≥800…<160 | ≥1600…<30 |
| | GSU | ≥650…<10 | ≥1000…<16 | ≥1600…<30 |
| V3 – Dangerous | Grid | ≥80 | ≥1600 | ≥3000 |
| | GSU | ≥1000 | ≥1600 | ≥3000 |

Table II – Concentration limit of dissolved gas

| Dissolved gas | Concentrations limit (ppm) | |
|---|---|---|
| | GSU | Grid Transformer |
| Hydrogen (H2) | 200 | 160 |
| Methane (CH4) | 100 | 60 |
| Ethane (C2H6) | 60 | 60 |
| Ethylene (C2H4) | 60 | 60 |
| Acetylene (C2H2) | 4 | 4 |
| Carbon-monoxide (CO) | 700 | 360 |
| Carbon-dioxide (CO2) | 10 | 10 |

The Standard offers the existence of three ratio codes presented in Table III (C2H2/C2H4, CH4/H2, C2H4/C2H6) to diagnose eight types of faults given in Table IV.

Table III – MSZ Standard's ratio for key gases

| Ratio limits | C2H2/C2H4 | CH4/H2 | C2H4/C2H6 |
|---|---|---|---|
| | Ratio codes | | |
| <0,1 | 0 | 1 | 0 |
| ≥0,1…1≤ | 1 | 0 | 0 |
| >1…3≤ | 1 | 2 | 1 |
| >3 | 2 | 2 | 2 |

Table IV – Fault diagnosis

| Case | C2H2/C2H4 | CH4/H2 | C2H4/C2H6 | Suggested fault diagnosis |
|---|---|---|---|---|
| 0 | 0 | 0 | 0 | Normal |
| 1 | 0 | 1 | 0 | Partial discharge of low-energy |
| 2 | 1 | 1 | 0 | Partial discharge of high-energy |
| 3 | 1-2 | 0 | 1-2 | Low energy arcing |
| 4 | 1 | 0 | 2 | High energy arcing |
| 5 | 0 | 0 | 1 | Hot spot 110°C…150°C |
| 6 | 0 | 2 | 0 | Hot spot 150°C…300°C |
| 7 | 0 | 2 | 1 | Hot spot 300°C…700°C |
| 8 | 0 | 2 | 2 | Hot spot above 700°C |

## IV. FUZZY LOGIC TECHNIQUE APPLIED TO DGA

Advantages of the application of fuzzy logic in fault gas analysis were published by several authors [3-5]. It was pointed out, that uncertainties of diagnosis due to the values close to limit values of classification procedures can be effectively handled by fuzzy sets. "Fuzzy version" of different methods, like Key gas analysis were made [5]. A typical solution is the application of a fuzzy inference system to approximate the relationship between the measured values and the faults causing the different gas combinations [5,6].

In this paper a method published before in [7] is used. Its application for fault gas analysis is presented through the National Standard's ratio method (however, it can be used in other methods as well). There are two important differences between the original method and the fuzzy logic based version. The first one is the application of fuzzy membership functions for the classification of fault gas ratios. It is important to remark, that setting the crossing of membership functions the degree of uncertainty can be taken into consideration. The second difference, that by the use of these functions, an upper and a lower limit is calculated for the specific faults. The rule base can be seen in Table V. Expression '-/low' means that the cell is not involved into the calculation of the maximal degree of existence while it is involved into the calculation of the minimal one. It is assumed that the appearance of fault gases and any not low ratios of the components (according to the National Stadard's ratio method) is a symptom, that is caused by the fault at the end of the row. A specific rule contains the fuzzy AND connection between the symptoms connected to a given fault.

Table V –Fuzzy logic rulebase

| C2H2/C2H4 | CH4/H2 | C2H4/C2H6 | Diagnosis |
|---|---|---|---|
| - / low | - / low | - / low | Normal |
| - / low | high | - / low | Partial discharge of low- |
| high | high | - / low | Partial discharge of high- |
| high / very | - / low | high / very | Low energy arcing |
| high | - / low | very high | High energy arcing |
| - / low | - / low | high | Hot spot |
| - / low | very high | - / low | Hot spot |
| - / low | very high | high | Hot spot |
| - / low | very high | very high | Hot spot above 700°C |

The method was used for different illustrative examples originated from the everyday practice, presented in Table VI. The result of analysis for the three different cases presented in Table VII

Table VI –Gas concentration for each case

| Dissolved gas | Case 1 | Case 2 | Case 3 |
|---|---|---|---|
| Carbon-dioxide(CO2) | 1300 | 4881 | 5963 |
| Ethylene (C2H4) | 1 | 113 | 36 |
| Ethane (C2H6) | 18 | 47 | 30 |
| Acetylene (C2H2) | 2 | 1 | 2 |
| Hydrogen (H2) | 394 | 80 | 50 |
| Methane (CH4) | 64 | 66 | 79 |
| Carbon-monoxide CO | 137 | 756 | 717 |

Table VII – Fuzzy logic diagnosis

| Diagnosis | Case 1 | | Case 2 | | Case 3 | |
|---|---|---|---|---|---|---|
| | minimal | maximal | minimal | maximal | minimal | maximal |
| Normal | 0 | 0 | 0 | 0 | 0,11 | 0,11 |
| Partial discharge of low-energy | 0 | 0,70 | 0 | 0 | 0 | 0 |
| Partial discharge of high-energy | 0,68 | 0,70 | 0 | 0 | 0 | 0 |
| Low energy arcing | 0 | 0 | 0 | 0 | 0,02 | 0,02 |
| High energy arcing | 0 | 0 | 0 | 0 | 0 | 0 |
| Hot spot 110°C…150°C | 0 | 0 | 0,80 | 1,00 | 0,11 | 0,55 |
| Hot spot 150°C…300°C | 0 | 0 | 0 | 0,20 | 0,45 | 0,90 |
| Hot spot 300°C…700°C | 0 | 0 | 0,21 | 0,20 | 0,55 | 0,50 |
| Hot spot above 700°C | 0 | 0 | 0,21 | 0,20 | 0 | 0 |

## V. IMPLEMENTATION OF FUZZY EXPERT SYSTEM

Expert system and fuzzy logic can take DGA methods and other human expertise to form a decision making system. Information such as the influence of transformer type, operation time, with or without on-load tap changer, voltage class, gassing rates and history of the diagnosis result can be utilized. A fuzzy expert system can reduce the uncertainties related to the oil sampling and chromatography analysis, avoiding the crispy limits between states considered in DGA methods. Figure 1 shows the suggested build-up of the system.

The transmission system substation equipments have been maintained and diagnostized by the National Power Line Company Inc. Substation Directory in Hungary. Moreover, the Substation Directory provides the same for a lot of other partner. To continue the maintaining provision on this high grade, and to comply with its maintenance functions to remain a reliable and competitive stakeholder of the market, the National Power Line Company Inc. had to introduce a better, more flexible, up-to-date registration of the committed equipments. Hence the National Power Line Company Inc. opted for introducing the substational machinery's maintenance and diagnostic data registry and maintenance task management system (asset management) namely "KarMen". The KarMen is able to manage the objects, machineries, assemblies and accessory parts; to store, visualize and track reports, diagnostic measurements data, lifetime and nascent documentation.

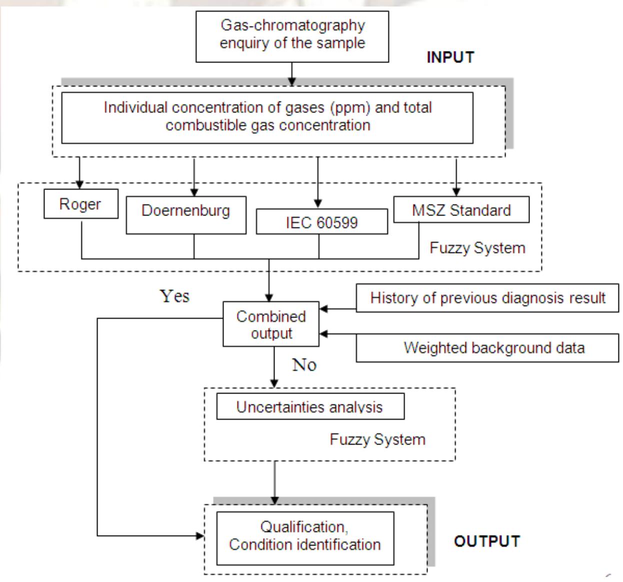
Besides managing the objects, object elements and related other modules, the main function of the application is to follow the lifecycle of the chosen object, equipment or assembly from the commissioning and adjustment tasks to exploitation and decommissioning.

The KarMen system – presented above – is able to manage the transformer's main parameters, and it does yeoman service to track continuously the lifecycle of them. It is feasible to assign object part to the objects, which also provides important information on DGA qualification. The diagram generator module of the application is capable to display only the amount of the gases, but it could not display the ratios and limits. The present knowledge base is focusing in two systems beside the professional experience. The LabSoft software which primary aims is to generate uniform, administration-supporting, user-friendly reports from the laboratory samples, and to archive the results. The other system is the KarMen which helps not only the Laboratory's, but the Substational Directory's tasks too, with containing the fingerprint's all of the equipment handled by National Power Line Company Inc. At present there is only one-way connection between Labsoft and KarMen, namely the DGA reports can be automatically downloaded from the Labsoft to the KarMen – it is compulsory in pursuance of National Power Line Company Inc.'s internal regulations. Nevertheless the report must be qualified when downloading it to KarMen. In the next phase of the research the new expert system will be connected into the present process on the grounds of the facts above:

1) Establish a system as an individual software or a module of the present application, which automatically comes into action after downloading the data, unburden the task of the qualifier.

2) Other way the expert system operating parallel with Labsoft but standing apart, which supports the report qualification process as a part of KarMen.

Figure 1 – Fuzzy expert system flowchart



## VI. ARTIFICIAL NEURAL NETWORK TECHNIQUE APPLIED TO DGA

Artificial intelligent (AI) techniques were studied worldwide recently for patter recognition such as fault diagnosis. These techniques include expert system, fuzzy logic and artificial Neural Network (ANN). ANN approach is automatically capable of handling highly nonlinear input- output relationships, acquiring experiences which are unknown to human experts from training data and also to generalize solutions for a new set of data. This feature will enable ANN to overcome some limitations of an expert system.

Another important function of ANN is its ability to interpolate and extrapolate from its experiences. This permits a best fit of the data, providing at least the best guess under the given circumstance, and avoiding the "no decision" problem sometimes occurs in the ratio methods [8].

The process of detection of incipient faults in transformers using an ANN can be seen as the process of associating inputs (patterns of gas concentrations) to outputs (fault types or normal condition) [9].

### A. *Input output patterns*

Neural network training requires the definition of input and output patterns.

The input data include all information related to an oil sample such as gas concentrations (H2, CH4, C2H2, C2H4, C2H6, CO, C02) and gassing rates, they are the key input parameters for diagnosis, the date of the oil sampling for calculating the gassing rates and other transformer information, like transformer type, size (capacity), with or without on-load tap changer etc.. For each input pattern there exists an output pattern which describes the fault type for a given diagnosis criterion.

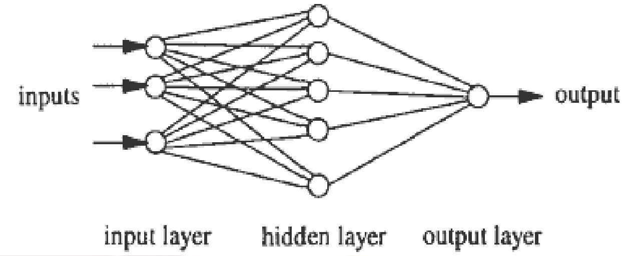
Diagnosis outputs include diagnosed fault type, diagnosis confidence and maintenance action recommendations. All the fault type classification are used in the system output, which were included in the previous DGA methods, such as no fault overheating, low energy discharge, high energy discharge - arcing and cellulose degradation. Both patterns constitute a neural network training set.

Input and output patterns for each diagnosis criterion (Roger, Doernenburg, IEC 60599, MSZ National Standard criterions) can be defined.

### B. *Neural network configuration and training*

Several ANN units are responsible for individual fault diagnosis. In the neural network, the most basic information-processing unit is the neuron model. They are organized in three or more layers, such as the input layer, single output and one or several hidden layers, use a back-propagation algorithm for training, presented in Figure 3. The number of neurons in the hidden layer was variable for each diagnosis criterion, depending on the problem complexity. Each neuron model receives input signals, which are multiplied by synaptic weights. An activation function transforms these signals into an output signal to the next neuron model and so on [10].

Figure 3 –Neuron model




## VII. CONCLUSION

Fuzzy logic and ANN based Power Transformer Fault Diagnosishas been presented.

It has been showed that using the fuzzy diagnosis method, more detailed information about the fault inside a transformer can be obtained. This is an improvement over the conventional ratio method, which may be due to the more realistic representation of the relationship between the fault type and the dissolved gas levels with fuzzy membership functions.

However, it has to be mentioned, that usually fuzzy inference systems are sensitive on the quality of the human knowledge base; appropriate membership functions and rules are necessary to obtain acceptable accuracy. On the other hand, fuzzy expert system needs a large knowledge base that must be constructed manually and cannot adjust their diagnostic rules automatically thus cannot acquire knowledge from new data samples through a self-learning process.

ANN approach can be used for this purpose since this method capable of automatically acquiring experiences from training data and the experiences they obtained includes not only those of human knowledge, but also those which may be still unknown to human experts. Thus, our further work to continue the research process on Artificial Intelligence (AI) to build-up a reliable diagnosis system using our plentiful database.

## VII. Acknowledgment

The authors thanks to MITS department Gwalior and Director Mr. Sanjeev Jain MITS Gwalior to continous encouragement to this work.

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