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Investigation on Sampling, Measurement and Interpretation of Gas-in-Oil Analysis for Power Transformers

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SUMMARY

This paper presents several aspects of sample storage, gas-in-oil extraction and analysis and interpretation techniques which are important for the diagnostic significance of the gas-in oil analysis results.

In conduction of DGA measurements, factors that affect the quality and reliability of gas-in-oil analysis have to be considered. Results of investigations on oil sampling techniques, as well as on different gas extractions techniques (vacuum extraction, equilibrium gas, shake test, headspace) and analyses by gas chromatography and photo acoustic spectroscopy techniques are presented. These different techniques are described and compared to each other.

Investigation of generation of fault gases in mineral oil under electrical and thermal faults in a laboratory set-up can improve the knowledge about type, amount and time dependency of gas generation.

Finally, in this paper DGA-interpretation is investigated. CIGRE Interpretation Scheme is used as an example to show deficiencies of conventional interpretation schemes. To overcome these limitations, DGA-interpretation is approached from the point of view of pattern recognition. The paper focuses mainly on classifier modelling and fault classification. Classifier modelling itself consists of 2 steps. At first classifiers are constructed based on CIGRE Interpretation Scheme and secondly constructed classifiers are trained according to IEC TC 10 database. To manage both construction and training, trainable fuzzy inference systems are introduced as a proper modelling tool. Untrained classifiers are multi-valued and are therefore able to estimate fault probability in percent. Trained classifiers have the additional advantage of a lower average classification error.

KEYWORDS

Power Transformer – Dissolved Gas Analysis – Oil Sampling – Condition Monitoring – Pattern Recognition – Trainable Fuzzy Inference System

1 INTRODUCTION

On account of deregulation of electricity generation and ageing of power transformers, there is an increasing concern to assess operating conditions of power transformers. Thus, Dissolved Gas Analysis (DGA) in a role of the most acknowledged fault diagnostic method has been widely applied for detection of incipient or potential faults, and thus for assessment of transformer condition. Within an effective oil analysis program, oil sampling, sample storage, analysis and interpretation techniques play significant roles to ensure reliable diagnosis of oil-filled power transformers [1].

2 STORAGE OF OIL SAMPLES

For reliable DGA analysis it is essential that trained personnel carries out oil sampling, storage and analysis correctly, following the guidelines described in IEC 60567 [2]. Due to lack of attention during management of oil sampling and storage, gas-in-oil concentrations can present significant deviations that may lead to misinterpretation of DGA and wrong diagnosis of faults in power transformers.

Factors that influence gas-in-oil concentrations of oil samples during storage are: air bubbles, light, temperature variation and storage time. These factors have been experimentally investigated by means of preparation of samples with air-saturated oil of new and aged condition, using glass syringes of 50 ml with airtight stopcocks. Samples were exposed to one of the influencing factors for certain period, in parallel the reference samples which were stored under similar conditions but without the effect of any influencing factor. Thereafter, gas-in-oil analyses were carried out at regular time intervals in order to evaluate the variation of gas-in-oil concentrations. Gas-in-oil analyses were carried out by a DGA measurement system that consists of Dynamic Headspace for gas extraction and Photo Acoustic Spectroscopy for gas analysis. In these experiments each sample was prepared in triplicate, and results of gas-in-oil analysis were normalized with respect to the concentration of reference samples. The measuring accuracy is within a tolerance range of ±5% [4].

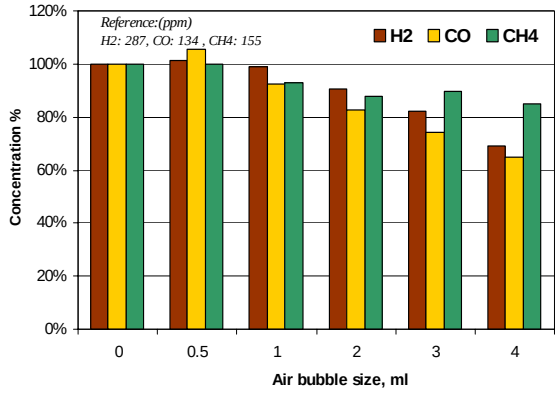

Fig. 1 Effect of air bubbles contained in samples

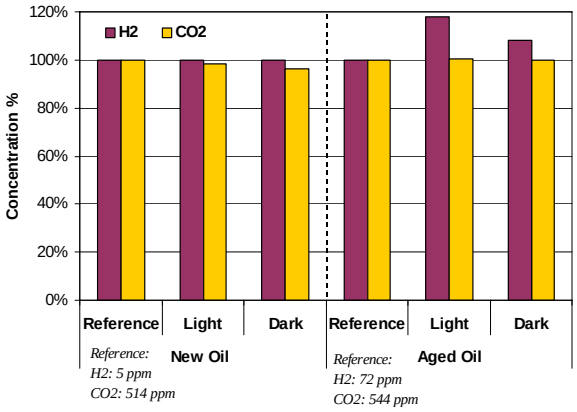

Fig. 2 Effected of light on samples stored for 8 days

Fig. 1 shows the variation of gas-in-oil concentrations for gas components that were most affected by air bubbles contained in sample syringes. For this experiment, oil samples were aged at 120°C for 8 days; thereafter concentrations of dissolved gases were analyzed which were defined as the reference. The oil was then sampled using syringes, which contained different volume of air bubbles and stored for 4 days before the DGA analysis. In general, the concentrations of these components tend to decrease, due to their relative low solubility in oil and thus fast diffusion into the air bubble. Therefore, air bubbles larger than 2% of the oil volume, i.e. 50 ml syringe, can cause significant variations of gas-in-oil concentrations, and hydrogen concentration can be reduced by approximately 35% when air bubble is larger than 8 % of oil volume. Fig. 2 shows the effect of light on stored samples of new and aged oil under room temperature. After 8 days, hydrogen and carbon dioxide presented the most considerable variations in their concentrations. In new oil, concentration of carbon dioxide presented a decrease by 12% approximately, that can be caused by the chemical equilibrium that involve carbonic acids of the oil composition. In case of aged oil, hydrogen concentration presented an increased of

approximately 13ppm (18%) by effect of light, that can be attributed to photochemical reactions that involve decomposition of aging products such as water and acids, and approximately 8% in the dark, due to possible chemical reactions that generate more gas.

Experimental investigation of storage at 60°C for 8 days resulted in concentration deviations of ±8 % for hydrogen, ±5 % for methane, ±14 % for ethane, and ±0.2 % for acetylene. These deviations can be due to possible chemical reactions and chemical equilibriums with by-products. Analysis of samples stored at 80°C for 20 days resulted in a significant increase of the concentrations of hydrogen, methane and carbon dioxide, until reaching a plateau; this phenomenon is known as 'stray gassing' and it is dependent on the type of oil. Regarding the effect of storage length, samples of aged oil taken from a power transformer were stored in dark at 20°C, without air bubbles and analyzed over a period of 16 days. Results of the gas-in-oil analysis presented maximum deviations of 3 % for carbon dioxide and below 1% for the rest of gas components. Therefore, oil samples stored up to 16 days in dark, room temperature and without air bubbles can guarantee repeatable results of gas-in-oil analysis.

3 DIFFERENT EXTRACTION TECHNIQUES FOR DGA

Along with correct sampling and storage of oil samples, effective extraction of gases dissolved in oil plays a key role for DGA. Table 1 presents different gas extraction techniques that have been utilized for investigation of their influence on final gas-in-oil concentration. Oil samples of the same oil type and the same gas-in-oil concentration were prepared. Hence, quantitative comparison of concentrations determined can provide insight into the efficiency and repeatability of these techniques. Higher concentrations in the gas phase means usually that a higher accuracy of the successive analysis technique can be achieved.

Table 1 Different Measurement Techniques for Dissolved Gas Analysis at 20 °C

Extraction Method	**Vacuum (VE)** [3]	**Syringe**	**Equilibrium gas head space (EGHS)** [4]	**Dynamic Headspace (DHS)** [5]
Techniques	4-step vacuum pump system	Vacuum and shaking with syringe	Column for oil circulation/air	Bottle for oil mixing/air
Gas Analysis	**G**as **c**hromatography (**GC**)	**G**as **c**hromatography (**GC**)	**G**as **C**hromatography (**GC**)	**P**hoto-**A**coustic **S**pectroscopy (PAS)

The vacuum extraction method (VE) uses a mercury-free 4-step vacuum pump to separate the gas from the oil. Equilibrium of gas phases in headspace can be achieved in closed static systems, or dynamic systems as the equilibrium gas headspace (EGHS) [5] and dynamic headspace (DHS) [4] methods, in which a gas phase is blown through a layer of moving liquid either by circulating or mixing. The headspace extraction is achieved by the diffusion of dissolved gases into the gas phase at constant temperature and pressure conditions until the equilibrium of coexistent phases is established according to Henry's law [6]. Thereby, with the concentration of components in the gas phase, and partial pressure of each gas component then the concentration of gases dissolved in oil can be determined.

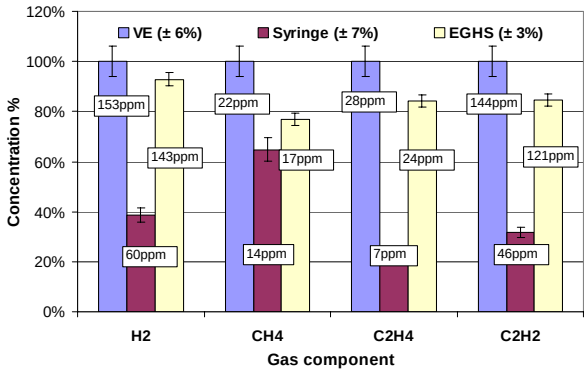

Fig. 3: Normalized concentrations obtained by different extraction methods

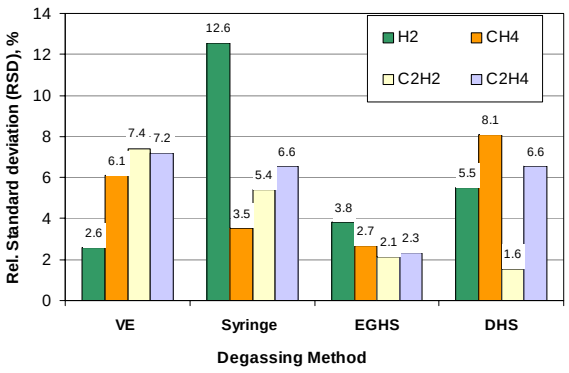

Fig. 4: Reproducibility of concentrations obtained by different extraction methods

The normalized concentrations of gas-in-oil of some representative components measured through different gas extraction techniques can be seen in Fig. 3. Vacuum Extraction and equilibrium headspace

yield the highest gas concentrations. Extraction by syringe displayed the lowest concentrations and higher deviations by far, however this method is subjected to include numerous operational errors that can lead to poor efficiency of extraction and large deviations.
Fig. 4 shows a graphical representation of the reproducibility of gas concentrations for four gases obtained by the techniques given in Table 1. The relative standard deviation (RSD)% was calculated based on 5 measurements of the same sample. Thus, it can be seen that hydrogen concentration was most accurately determined by vacuum degassing, with the lowest relative standard deviation of 2.6%. The EGHS method showed quite low deviations for all components, which can be attributed to the time to reach the equilibrium state and stable pressure and temperature conditions. The highest relative standard deviation (12.6 %) was obtained for hydrogen with the syringe method; this is due to numerous and unavoidable operational errors inherent to the extraction by syringe, i.e. shaking time, time to reach equilibrium of gas-oil phase, leaks, personnel experience and etc.

4 INVESTIGATION OF GAS GENERATION

When an incipient fault occurs in a transformer, the oil or oil-cellulose insulation surrounding the fault would experience decomposition and generate gases. It is assumed that the gas generation sustains steadily and as a consequence the amount of gases in oil would be accumulated to a detectable level by DGA analysis. The generation rate for a slowly developing fault, can be simply determined by periodical samplings. However, other factors such as dynamic gas distribution between oil and gas space, the differences between free breathing and sealed transformers, absorption of gas by cellulose insulation, and loading/temperature fluctuation would affect the DGA results making determination of gas generation rate a more complex matter. The affecting factors mentioned above, although many, are all related to gas partition and 'equilibrium', which is hardly achievable in an operating transformer environment.
To help our understanding of gas generation under faults in transformers, overheating, hotspots and low-energy discharge faults were generated with laboratory oil-cellulose insulation samples. 10GBN was the mineral oil and Weidmann paper tape was the cellulose under the tests. A fault was generated and sustained for different time spans, afterwards oil samples were taken using sampling syringes and DGA results obtained through Topler vacuum extraction method.
Under 120°C, samples of 85 ml mineral oil were sealed in a 100 ml bottle, leaving a 15ml gas space being purged with Argon; when cellulose is involved, a weight ratio of 20:1 was used for oil-cellulose and their volume was maintained as a total of 85 ml. A six-month oil-paper ageing program was performed and oil DGA results and fault gases in gas space were obtained, as given in table 2.

Table 2 Measured Gas- in- oil and Gas-in-gas space Values (in ppm) due to Sealed Ageing at 120°C

Month	**H2**		**CH4**		**C2H6**		**C2H4**		**C2H2**		**CO**		**CO2**	
	GS	**DGA**	**GS**	**DGA**	**GS**	**DGA**	**GS**	**DGA**	**GS**	**DGA**	**GS**	**DGA**	**GS**	**DGA**
1	0	0	275	111	39	125	5	11	0	0	994	92	4405	5324
2	76	9	37	21	14	44	10	22	0	0	1574	281	3728	5383
4	23	7	67	30	10	33	11	22	0	0	2537	303	7827	9383
5	178	16	81	53	6	25	8	24	0	0	4061	769	7274	12565

During the 1st month, 'straying' gases may be generated, which gives higher values of methane and ethane and most of the methane diffused into the gas space. Along the ageing months at 120°C methane and ethane increase steadily in amount while ethylene remains fairly constant, i.e. ~20 ppm dissolved in oil and ~10 ppm in the gas space. The first reading of hydrogen as zero is a false reading which shows the uncertainty and difficulty when measuring small amount of this easy-escape gas.
120°C is high for cellulose paper and DGA results such as carbon monoxide and carbon dioxide are the indicators for paper overheating, the generation amount in ppm value is calculated by adding the gas-in-the-gas-space and the gas-in-oil together, and the generation rate is shown in Fig. 5. Under 120°C, a relative low temperature for overheating or a reasonable temperature for overloading, the amount of carbon dioxide generated is about 9-23 times higher than the amount of carbon monoxide. Within two months of ageing under 120°C, the DP of paper samples was reduced from ~1000 to ~300, and at the

end of six months, the DP was reduced to 150, meanwhile the value of 2-FAL in the oil was measured as around 10ppm at the end of two months, and increased to 30ppm at the end of the six months ageing period.

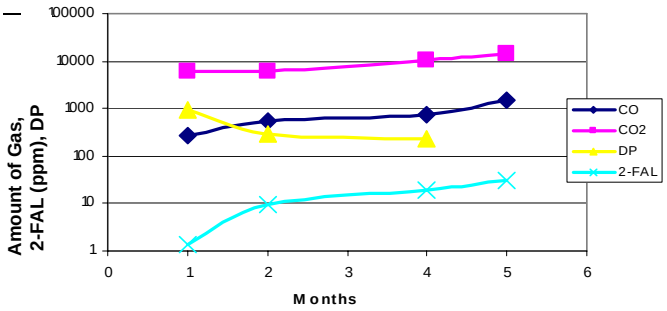

Fig. 5: Gas generation in relation to DP reduction and 2-FAL increase

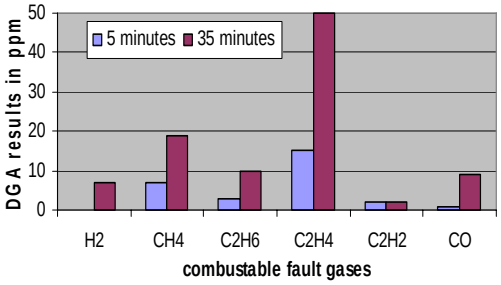

Fig. 6: Combustable gases generated under 500-700°C and different fault periods

For thermal faults near to conductor, a test rig is built to simulate a high temperature fault in the laboratory. The conductor is immersed deep in oil and its temperature was maintained in a range between 500-700°C for both 5 minutes and 35 minutes time spans. The tests were conducted with an open test vessel, in view of the laboratory 'safe working' regulation. Fumes were generated and fanned out during the test period, oil samples were taken at the end of each test and the DGA results are given in Fig.6.

Again, for the 5 minutes experiment, hydrogen reading was as zero indicating the difficulty in obtaining and measuring this easy-escape gas. Nevertheless among the total combustible gases generated, ethylene became the dominant gas, both in ppm and in percentage (>50% in the TDCG).

As many literatures rightly pointed out, many high temperature thermal faults involve paper insulated conductors. Consequently it is in our plan to extend this test scheme using paper wrapped conductor to create overheating conductor effect.

For electrical faults, three breakdowns were generated using a point-plate electrode configuration with a 10 mm oil gap. The AC breakdown voltages were averaged as 40 kV. The energy was reasonably controlled by the secondary over-current protection relays, therefore a limited power-through spark was created at the centre of the sealed test vessel which was filled with 1.5 litre oil. Immediately after three sparkings the circulation pump was switched on which accelerated the equilibrium process of gases from the localised sparking point to the whole volume of oil. Prior to circulation, oil samples were taken through valves located at the bottom and the mid vessel and the DGA results are given as in Fig. 7. It can be seen that a significant amount of acetylene and hydrogen was generated due to the sparking, and local temperature near to the breakdown is significantly high which helps to create ethylene also.

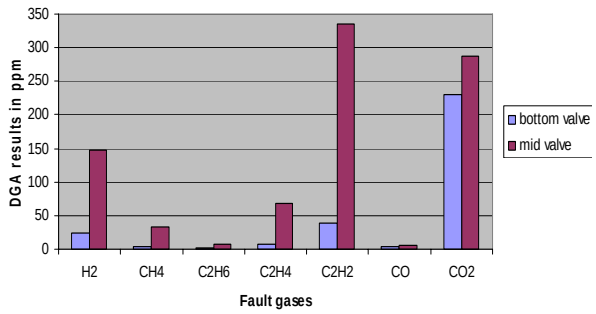

Fig. 7: Gas generated during a sparking electrical fault- sampled at different locations

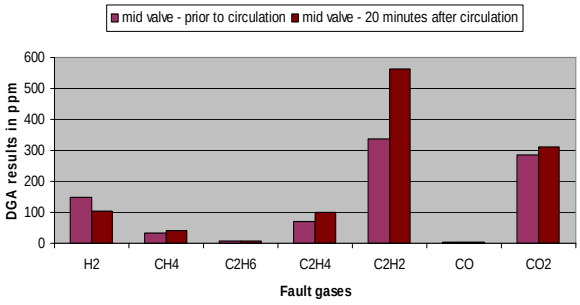

Fig. 8: Gas generated during a sparking electrical fault- sampled at different time;effect of circulation

These results given in Fig.7 show that the gas concentration at different locations would be quite different, i.e. gases tend to move up due to the light gravity and are dissolved into the oil while they are travelling. After 20-minutes circulation time, oil samples were taken again at the mid valve and the DGA results are compared in Fig.8 to the previous sample to show the equilibrium process.

5 TRAINABLE FUZZY INFERENCE SYSTEM FOR DGA-INTERPRETATION

Condition assessment is an application area for pattern recognition. In the process of pattern recognition one can distinguish two phases: modelling phase and detection phase, as depicted in Fig. 9.

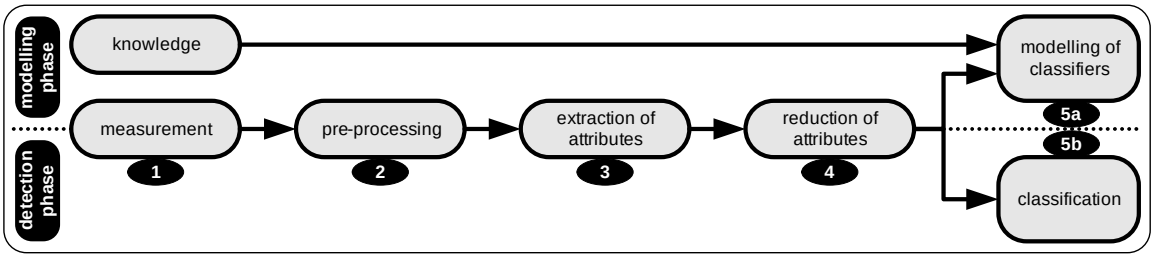

Fig. 9: Modelling phase and detection phase in the process of pattern recognition

Both phases have steps in common: the 1st step is called measurement and is already described in detail in the previous chapters. In the case of DGA the purpose of measurement is to monitor dissolved gases in oil. Pre-processing of measured data occurs in step 2 which means for example averaging to reduce noise or the application of thresholds that control processing of succeeding steps. Step 3 focuses on the extraction of attribute-carrying variables. For DGA, attribute-carrying variables are key gases, key gas sums and key gas ratios. Key gas sums and key gas ratios cannot be extracted at that level, so first mathematical transformations have to be applied to key gases, namely addition and division. The purpose of step 4 is to reduce attribute-carrying variables of step 3 to a bare minimum that are necessary for modelling of each classifier in step 5a and classification of faults in step 5b.
Cigré task force 15.01.01 suggested an interpretation scheme for DGA that uses two types of attribute-carrying variables, namely key gas ratios and key gases or alternatively key gas sums, to make statements in view of transformer faults [7]. Reliable information is provided in case both types of attribute-carrying variables are below or above a certain threshold, but not in the other cases. Furthermore, **C**IGRE **I**nterpretation **S**cheme (CIS) does not work with multi-valued logic so it is unable to provide gradual instead of binary-valued fault information.
Taking partial discharge faults as an example, the modelling of classifiers (5a) will be explained. Trainable fuzzy inference systems will act as a modelling tool to overcome all above mentioned limitations. Finally, classification (5b) in the case of partial discharge (PD), discharge (D) and thermal fault (T), will show the improvements of the so modelled classifiers in comparison to CIS.

5.1 Modelling of improved fault classifiers with trainable fuzzy inference systems

In the subject of pattern recognition different modelling tools are available [8]. Among all them there is one named trainable fuzzy inference system (T-FIS). T-FIS is a tool to model with empirical knowledge. Moreover T-FIS is trainable with reliable data samples and implicit multi-valued. All attributes are very useful to overcome CIS limitations mentioned above.
But prior to classifier modelling with T-FIS and subsequent classification, pattern recognition runs through steps 1-4 according to Fig. 9. At first dissolved gases are measured (1), namely H_2, CH_4, C_2H_2, C_2H_4, C_2H_6, CO and CO_2. Pre-processing (2) is not needed in this case. Next, all attribute-carrying variables are extracted or otherwise calculated (3), by name: H_2, C_2H_2, $CH_4+\sum_{x=2,4,6}C_2H_x$, $\sum_{x=1,2}CO_x$, C_2H_2/C_2H_6, H_2/CH_4, C_2H_4/C_2H_6, CO_2/CO, C_2H_2/H_2. In case of PD-classifiers attribute-carrying variables have to be reduced to H_2 and H_2/CH_4 (4).
Classifier construction: Classifier modelling with T-FIS means at the very beginning construction by means of empirical knowledge, which is taken from the CIS even though it is binary-valued [9]. Structure and behaviour of the PD-classifier is shown in Fig. 10a. The PD-classifier uses H_2/ppm and H_2/CH_4 ratio as input variables and PD/% as the output variable. For input variables rectangular membership functions are used to clone the effect of CIS thresholds. For the output variable singleton membership functions are used. As above mentioned, fault detection in CIS is only reliable for the cases where both types of attribute-carrying variables are below or above a certain threshold. Translating that into the structure of T-FIS that is used for PD-classifier construction means that only for the cases where both H_2 and H_2/CH_4 are either small or large T-FIS is reliable. Thus, only μ_{ss}(PD) and μ_{ll}(PD) are

defined according to CIS and only corresponding rule weights are defined as 1. μ_{sl}(PD) and μ_{ls}(PD) are defined arbitrarily in between μ_{ss}(PD) and μ_{ll}(PD) but with small rule weights of 0.1.

Classifier training: Next to construction, training is used to incorporate training samples into T-FIS. Training presumes a standardised T-FIS. So classifiers have to be standardised before training. For simplicity standardisation is not addressed here.

Besides the usage of training samples, training has also to consider empirical knowledge taken from CIS during construction. Thus, prior to training, each rule of the T-FIS has to be converted into an equal amount of additional training samples. The amount of training samples is defined by rule's weight with the help of a conversion factor. In this example the conversion factor is 10, so as a rule with a rule weight of 1 equals to 10 training samples. The training algorithm calculates the arithmetic mean of the all training samples in order to estimate the expectancy value of samples to be classified later. As a result, rule weights and singleton membership functions of T-FIS' output variable become properly adjusted.

As training samples only measurement values are used for which the corresponding fault type is confirmed by inspection as given in the IEC TC 10 database [10]. This database provides tables for three fault types: one table for PD, two tables for D and two tables for T. Training samples either partially confirm or adjust the PD-classifier as can be seen in Fig. 10b. So training confirms the reliable rule for $H_2 \leq 100$ and $H_2/CH_4 \leq 10$ and adjusts all other rules. According to the amount of contributing sample vectors to the training of each rule the corresponding rule weight is increased. An increased rule weight denotes improved rule reliability.

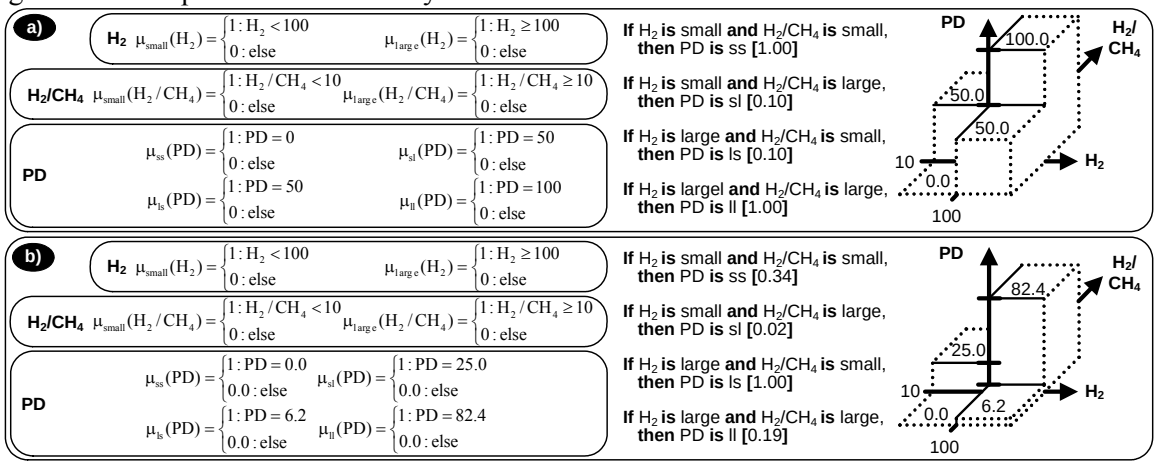

Fig. 10: PD-classifier before training a) and after training b)

5.2 Advanced fault classification

In order to show the performance of classifiers before and after training data from the IEC TC 10 database [10] are used. Table 3 shows these DGA data sets together with the output of CIS and the simultaneously applied PD-, D- and T-classifiers that are once untrained and once trained. The probability of each fault is given in percent. The second row shows a typical DGA signature for a discharge. CIS and the untrained T-classifier fail once in this case, because thermal fault is classified additionally (marked in red). The trained classifier shows an estimated probability of 97.4% for discharge and 40.4% for thermal fault. This result reveals discharge as the cause of fault, but the high probability for thermal fault shows the low significance of the conclusion. The comparison of untrained and trained classifiers of type PD and D show a lower average error of trained classifiers.

Table 3 Faults of IEC TC 10 database classified by CIS as well as by untrained and trained classifiers

H_2 ppm	CH_4 ppm	C_2H_2 ppm	C_2H_4 ppm	C_2H_6 ppm	Partial Discharge (PD)			Discharge (D)			Thermal Fault (T)		
					CIS	un-trained	trained	CIS	un-trained	trained	CIS	un-trained	trained
Type of fault: Partial discharge													
37800	1740	8	8	249	true	100	82.4	false	0	2.7	-	50	20.8
Type of fault: Discharge													
305	100	541	161	33	-	50	6.2	true	100	97.4	true	100	40.2
210	43	187	102	33	-	50	6.2	true	100	97.4	-	50	20.5
Type of fault: Thermal fault													
3420	7870	33	6990	1500	-	50	6.2	-	50	3.8	true	100	40.2
6709	10500	750	17700	1400	-	50	6.2	-	50	3.8	true	100	40.2

6 CONCLUSION

Experimental results showed that air bubbles larger than 2% of the oil volume could cause significant variations of gas-in-oil concentrations in oil samples. Hydrogen concentration can be reduced up to 35% for air bubbles larger than 8% of oil volume. Storage at 60°C or 80°C can lead to strong variations of gas-in-oil concentrations due to ongoing chemical reactions, e. g. stray gassing or chemical equilibrium with ageing products. Storage of samples in a dark place at 20°C and without air bubbles can guarantee gas-in-oil concentrations with variations below ± 1%. Vacuum extraction and dynamic headspace showed similar results concerning amount of gases and repeatability. Extraction by syringe resulted in high deviations.

The investigation of generation of fault gases in mineral oil under electrical and thermal faults in a laboratory set-up can improve the knowledge about type, amount and time dependency of gas generation.

Trainable fuzzy inference systems are an advantageous tool to model fault classifiers for DGA-interpretation. First, due to the fact that trainable fuzzy inference systems are implicit multi-valued, classifiers can estimate the fault probability in percent. Second, classifiers profit from bi-parted modelling: Construction considers empirical knowledge from Cigré Interpretation Scheme while training takes reliable training samples from IEC TC 10 database into account. Both together reduce the average error of classification of such modelled classifiers and therefore improve classifiers' accuracy.

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