Fuzzy-Logic Applications in Transformer Diagnosis Using Individual and Total Dissolved Key Gas Concentrations

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***Abstract*—The gases generated in oil filled transformer can be used for determination of incipient faults. Dissolved gas analysis (DGA) of transformer oil has been one of the most powerful methods to detect the faults. The various methods such as liquid chromatography, acoustic analysis, and transformer function techniques require some experience to interpret observations. The researchers have used artificial intelligence (AI) approach to encode these diagnostic techniques. This paper presents an expert system using AI techniques which can diagnose multiple faults in a transformer theoretically and practically using fuzzy-logic information model. We also concluded by identifying limitations, recent advances and promising future research directions over seventy and more power transformers.**

***Keywords*— Transformer, Dissolved gas analysis, Fuzzy-logic, diagnostic, Expert system**

I. Introduction

Reliable and quality power is need of the hour for the economic development of a country. For providing reliable electrical energy, it is very necessary to have highly reliable associated electrical equipments in electrical power stations. The transformer, being key element in the transmission and distribution of electrical energy need special care [1]. For improving its satisfactory operation under normal power system conditions, the system reliability is of utmost importance. Large oil filled electrical power equipments, such as transformers and reactors, is a critical element of an electrical power system. The reliability and continuous performance of these equipments is then vital key to the profitable generation and transmissions. To minimize the capital expenditure of the electrical power system, it is very common to operate these equipments at or close to the limits of their design parameters [2]. Power transformers are the vital link of the power system. Monitoring and diagnosis techniques are essential to decrease maintenance and improve reliability of equipment [3]. Due to highly competitive electrical energy market it is required to enhance the system's reliability and availability with cost effectiveness. To maintain higher system reliability, its key components such as power transformer is required to undergo periodic diagnostics and reduce its losses for effective utilization of capital resources.

In the presented paper an attempt has been made to present the various conventional and non-conventional DGA methods [1, 4, 7] used by various agencies and utilities to find the condition of the cellulose material within an in-service transformer. The various Artificial Intelligence (AI) Techniques [8-17] that have been used by the researchers in the past have been considered and some conclusions have been drawn based upon the observations.

Fuzzy logic with fuzzy-logic IF-THEN rules firing scheme have been used to analyze the health condition of power transformers. The extracted data from DGA has been used for fuzzy-logic input and output membership function and the best parameters for this network have been presented graphically. Finally result given by fuzzy logic expert system has been compared with IEEE/ANSI standards.

II. Fuzzy-Logic

Fuzzy-Logic (FL) is a relatively new artificial intelligence technique. FL means approximate reasoning, information granulation, computing with logical words and so on. Fuzzy systems are rule-based systems that are constructed from a collection of linguistic rules. FL is a convenient way to map an input space to an output space. It provides mathematical strength to the emulation of certain perceptual and linguistic attributes associated with human cognition. The theory of fuzzy logic provides an inference mechanism under cognitive uncertainty. This view of network as a parameterized function will be the basis for applying standard function optimization methods to solve the problem of neural network training.

A. Expert System for Transformer Diagnosis:

The schematic diagram of fuzzy logic transformer diagnosis (FLTD) expert system is shown in Fig.1. FLTD is a novel fuzzy-based approach that deals with heterogeneous data of both linguistic and numeric types, imprecise, vague in-formation, and concepts encountered in the mechanical-fit process and facilitate the expression of the reasoning process of an experienced observer with minimal rules.

The Fuzzy Logic Transformer diagnosis process represents a fuzzy-logic-based complete transformer diagnosis process comprising the following three phases:

phase I: tentative selection of total dissolved combustible gas (TDCG), and TDCG_rate;

phase II: mechanical-fit process and;

phase III: estimate the Sampling Interval (SI), and operating Procedure (OP) for transformer.

A general schematic of FLTD representing the second phase is shown in Fig. 1. It involves the following phases:

1) Fuzzification;
2) Knowledge representation;
3) Inference scheme;
4) Defuzzification.

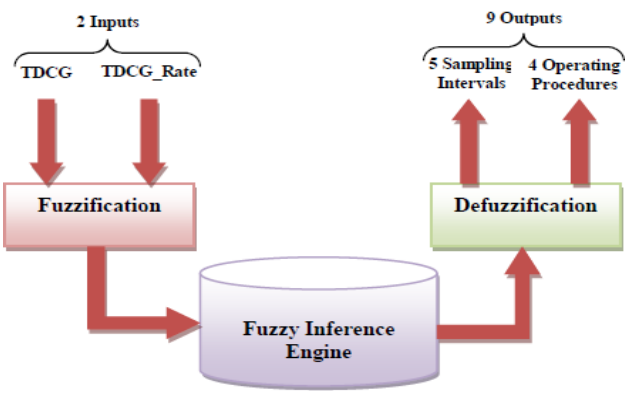


Figure 1: General scheme for FLTD

TDCG = $C_2H_2 + C_2H_4 + H_2 + CH_4 + C_2H_6 + CO$ *(1) and*

TDCG_Rate = *(St-So)/T* *(2)*

Where *St* = Current TDCG; and *So* = Previous TDCG

T = Time duration in days.

For example, data taken of sample no. 5 from Table 3 as H_2=16ppm, CO=935ppm, C_2H_4=28ppm, C_2H_6=6ppm, CH_4=12ppm, C_2H_2=29ppm, then TDCG = 1026 ppm (using formula 1).

Assume that the previous TDCG is 630 ppm for sample no. 5, and the duration from last sampling date is 30 days. The TDCG rate can be calculated using formula 2 as:

TDCG_Rate= (1026-630)/30

= 13.2

In the similar way TDCG_rate can be calculated for all samples of Table No. 3.

In Section "B", membership function of input and output variables for fuzzy FLTD expert system are discussed. Section III describes the FL based simulation and result.

B. Input and Outputs of Fuzzy-Logic System:

Total Dissolved Combustible Gas (TDCG) in transformer fault detection concept is useful in finding out the suitable oil-sampling interval based on the health condition of the transformer so as to compensate the conflict between excessive cost due to over sampling and neglected danger owing to long sampling period. In general, TDCG uses the sum of the 6 key gas values (as formula 1) and the TDCG gas generation rate to determine the operating procedure and predict suitable oil sampling interval as shown in Table 1 [19].

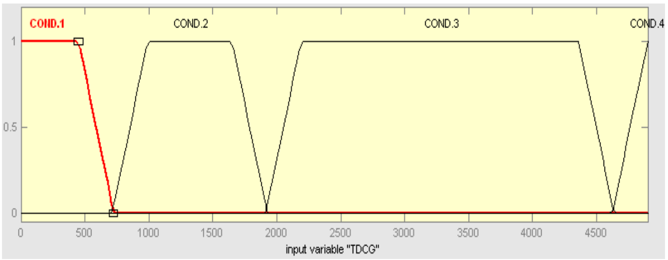
Table 1

Action Based on Dissolved Combustible Gas as per [19]

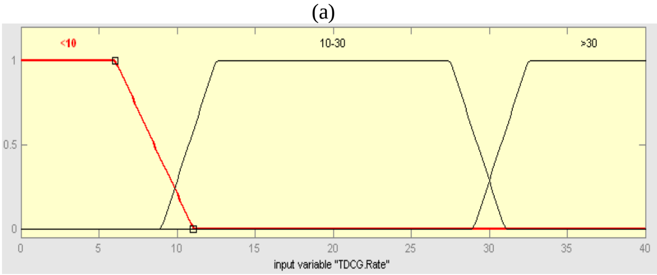
Status/ TDCG	**TDCG_Rates (ppm/day)**	**Sampling Intervals and Operating Procedures for Gas Generation Rates**	
		Sampling Interval (SI)	**Operating Procedure (OP)**
Condition 1 <720	<10	6 Monthly (SIA)	Continue normal operation (OPA)
	10-30	Quarterly (SIQ)	
	>30	Monthly (SIM)	Exercise caution. Analise individual gases to find cause. Determine load dependant (OPB)
Condition 2 721-1920	<10	Quarterly (SIQ)	Exercise caution. Analise individual gases to find cause. Determine load dependant (OPB)
	10-30	Monthly (SIM)	
	>30		
Condition 3 1921-4630	<10	Monthly (SIM)	Exercise caution. Analise individual gases to find cause. Plan outage. (OPC)
	10-30	Weekly (SIW)	
	>30		
Condition 4 >4630	<10	Weekly (SIW)	Exercise caution. Analise individual gases to find cause. Plan outage. (OPC)
	10-30	Daily (SID)	
	>30		Consider removal from service

Although the TDCG method is widely used in solving fault diagnosis problem, but in the certain cases, it is very hard to determine the correct group of the TDCG value especially when the TDCG value falls near the boundary line as shown in the TDCG rules set in Table 1. The fuzzy logic technique is advantages in solving this problem, which is explained in section III.

For the TDCG diagnostic method, the sum of the six fault gases and the gas generation rate are required to determine the health condition of a power transformer. Based on these results, a fuzzy model is developed using its input variable, TDCG, and TDCG_Rate. Membership functions (MF) for input variables are established based on the variation of TDCG, and TDCG_Rate as shown in Fig. 2(a-b). The membership functions for the output variables (expected diagnosis such as SI and OP) are shown in Fig 2(c-d).



(a)



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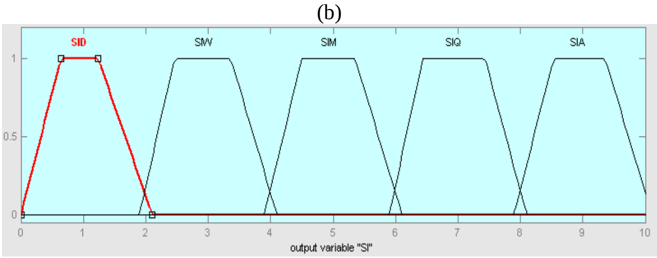

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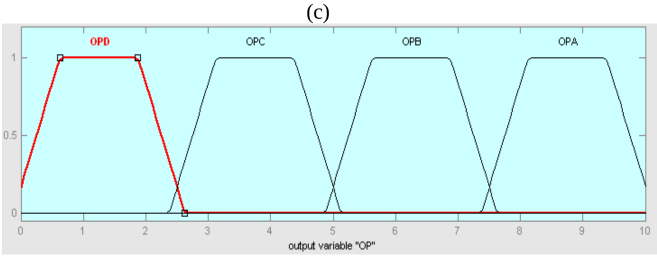

(d)

Fig. 2: Trapezoidal membership functions: (a) input variable of TDCG; (b) input variable of TDCG_Rate; (c) output variable of SI; (d) output variable of OP.

Based on the experimental results, a set of fuzzy rules relates the input linguistic variables to the output are developed as shown in Table 2. The expected diagnosis for transformer using input variables is shown in Fig. 3. The 3D surface viewer outputs for SI and OP with respect to (w.r.t.) TDCG and TDCG_Rate are shown in Fig. 4 and Fig. 5 respectively.

Table 2
Fuzzy inference rules for Transformer Health

Rule 1	**If (TDCG is COND.1) and (TDCG_Rate is <10) then (SI is SIA)(OP is OPA)**
Rule 2	**If (TDCG is COND.1) and (TDCG_Rate is 10-30) then (SI is SIQ)(OP is OPA)**
Rule 3	**If (TDCG is COND.1) and (TDCG_Rate is >30) then (SI is SIM)(OP is OPB)**
Rule 4	**If (TDCG is COND.2) and (TDCG_Rate is <10) then (SI is SIQ)(OP is OPB)**
Rule 5	**If (TDCG is COND.2) and (TDCG_Rate is 10-30) then (SI is SIM)(OP is OPB)**
Rule 6	**If (TDCG is COND.2) and (TDCG_Rate is >30) then (SI is SIM)(OP is OPB)**
Rule 7	**If (TDCG is COND.3) and (TDCG_Rate is <10) then (SI is SIM)(op is OPC)**
Rule 8	**If (TDCG is COND.3) and (TDCG_Rate is 10-30) then (SI is SIW)(OP is OPC)**
Rule 9	**If (TDCG is COND.3) and (TDCG_Rate is >30) then (SI is SIW)(OP is OPC)**
Rule 10	**If (TDCG is COND.4) and (TDCG_Rate is <10) then (SI is SIW)(OP is OPC)**
Rule 11	**If (TDCG is COND.4) and (TDCG_Rate is 10-30) then (SI is SID)(OP is OPC)**
Rule 12	**If (TDCG is COND.4) and (TDCG_Rate is >30) then (SI is SID)(OP is OPD)**

However, this method can not specify the type of fault that occurs in the transformer. This method is only able to detect whether the transformer is in good or bad condition which is imported for maintenance scheduling.

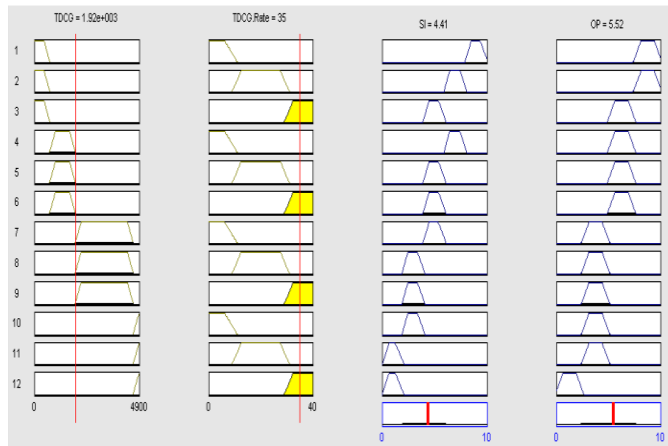

Fig. 3: Test results of fuzzy transformer diagnosis with trapezoidal membership function

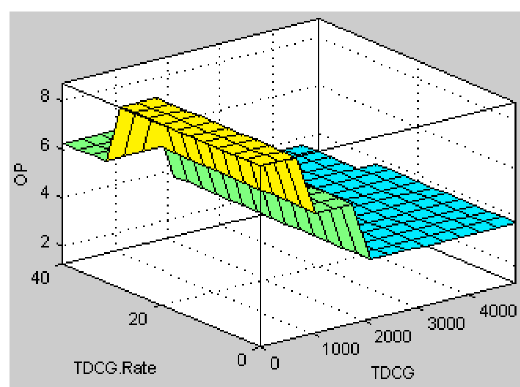

Fig. 4: Surface viewer of OP w.r.t. TDCG and TDCG_Rate

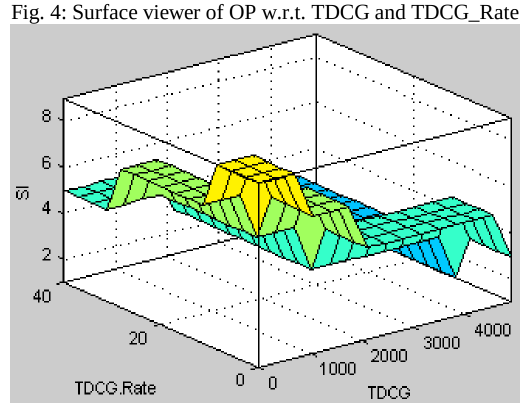

Fig. 5: Surface viewer of SI w.r.t. TDCG and TDCG_Rate

III. Results and Discussion

Using fuzzy logic method, seventy numbers of 6.3-52 MVA, 50 Hz, having voltage ratio 220/11kv, 132/33kv, 132/11kv, 66/11kv power transformers of Himachal Pradesh State Electricity Board (HPSEB), India were diagnosed and some typical results are given in Table no. 3. These results are taken by using Kalman Transport-X DGA analyzer. For this method, 4 operating procedures (OP) and 5 sampling intervals (SI) are determined by choosing the highest degree of membership value obtained from the fuzzy inference rules. The operating procedure and sampling interval can be classified into the linguistic variable based on the degree of membership function as shown as Table 5(a) and 5(b).

Table 3
Transformer gas concentration for fault diagnosis-Test data

S. N.	H_2	CO_2	CO	C_2H_4	C_2H_6	CH_4	C_2H_2	TDCG
1	6	2552	295	27	137	79	<0.5	544
2	<5	2261	51	63	160	4	2	280
3	10	8185	358	21	84	18	16	506
4	7	9320	726	327	106	171	<0.5	1337
5	16	5004	935	28	6	12	29	1026
6	1866	229	10	111	2	64	1265	3318
7	1879	198	6	36	5	29	521	2477
8	505	2626	340	817	82	256	881	2881
9	3619	2395	41	80	4	61	900	4705
10	3524	103	10	115	4	69	1163	4885

Table 4
Action Based on Fuzzy-Logic and comparison with IEEE Std.

TRF N0.	TDCG	TDCG _Rate	Action for Gas Generation Rate as per IEEE Std. C57.104		Action for Gas Generation Rate as per Fuzzy Logic	
			Sampling Interval **(SI)**	Operating Procedure **(OP)**	Sampling Interval **(SI)**	Operating Procedure **(OP)**
1	544	<10	SIA	OPA	8.98-8.99	8.75
		10-30	SIQ		6-7.84	7.9-8.75
		>30	SIM	OPB	4.98	6.25
2	280	<10	SIA	OPA	8.98-8.99	8.75
		10-30	SIQ		6-7.84	7.49-8.75
		>30	SIM	OPB	4.97-4.98	6.25
3	506	<10	SIA	OPA	8.98-8.99	8.75
		10-30	SIQ		6-7.84	7.79-8.75
		>30	SIM		4.97-4.98	6.25
4	1337	<10	SIQ		6.97-6.99	6.25
		10-30	SIM		4.97-5.85	6.25
		>30		OPB	4.97-4.98	6.25
5	1026	<10	SIQ		6.97-6.99	6.25
		10-30	SIM		4.97-5.85	6.25
		>30			4.97-4.98	6.25
6	3318	<10			4.97-4.99	3.75
		10-30	SIW		2.96-3.84	3.75
		>30			2.96-2.98	3.75
7	2477	<10	SIM		4.97-4.99	3.75
		10-30	SIW		2.96-3.84	3.75
		>30		OPC	2.96-2.98	3.75
8	2881	<10	SIM		4.97-4.99	3.75
		10-30	SIW		2.96-3.84	3.75
		>30			2.96-2.98	3.75
9	4705	<10			2.99	3.75
		10-30	SID		1.03-1.9	2.51-3.75
		>30		OPD	1.03	1.26
10	4885	<10	SIW	OPC	2.96-298	3.75
		10-30	SID		1.01-1.9	2.51-3.75
		>30		OPD	1.01-1.02	1.25

It has been observed from the Table no. 4 that the new method is generally in agreement with ANSI/IEEE method for power transformers diagnosis. Compared with ANSI/IEEE C57.104 method, the fuzzy logic method also has some advantages. For example, due to no matching condition, five transformers could not be diagnosed by the ANSI/IEEE method but are diagnosed by the fuzzy logic method. In some cases, the deterioration of insulating paper may be only at the early stage or intermittent which did not produce sufficient gases to give a stronger indication. However, such information obtained should be useful for future trend analysis.

Table 5(a)
Transformer gas concentration for fault diagnosis

Membership Degree (out of 10) of Fuzzy output Result for SI		Membership Degree (out of 10) of Fuzzy output Result for OP	
SIA	>8		
SIQ	6.0-7.84	OPA	>7.45
SIM	4.97-5.85	OPB	6.25
SIW	2.96-3.84	OPC	3.75
SID	<1.9	OPD	<1.29

Table 5(b)
Transformer gas concentration for fault diagnosis

Degree of Membership (out of 1)	Condition
1	Most Encourageable
0.75 – 0.99	Encourageable
0.5 – 0.74	Preferable

Let us an example for Interpretation:
Most Encourageable operating procedure:
Exercise caution. Analyse for individual gases. Plan outage
Preferable sampling interval: Weekly.

IV. Conclusion

This paper has presented a framework for performing diagnostics using fuzzy-logic expert system. FL techniques has provided efficient solution to decide the sampling interval (SI) of transformer oil and operating procedure (OP) for maintenance in transformer. FL has emerged over the years and had made remarkable contribution to the various fields of engineering. In fact, they have already been successfully applied in many industries. In case of Electrical systems, the models presented by FL are tested and practically used. They have solved many different categories of faults analysis. A lot of research is still required in order to understand electrical system behaviour.

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