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A Novel Association Rule Mining with IEC Ratio Based Dissolved Gas Analysis for Fault Diagnosis of Power Transformers

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Abstract

Dissolved gas Analysis (DGA) is the most important component of finding fault in large oil filled transformers. Early detection of incipient faults in transformers reduces costly unplanned outages. The most sensitive and reliable technique for evaluating the core of transformer is dissolved gas analysis. In this paper we evaluate different transformer condition on different cases. This paper uses dissolved gas analysis to study the history of different transformers in service, from which dissolved combustible gases (DCG) in oil are used as a diagnostic tool for evaluating the condition of the transformer. Oil quality and dissolved gasses tests are comparatively used for this purpose. In this paper we present a novel approach which is based on association rule mining and IEC ratio method. By using data mining concept we can categorize faults based on single and multiple associations and also map the percentage of fault. This is an efficient approach for fault diagnosis of power transformers where we can find the fault in all obvious conditions. We use java for programming and comparative study.

Keywords

DGA, ROGERS's ratio Method, IEC Method, Data Mining, Association Rule Mining.

I. Introduction

Power transformers are designed to transmit and distribute electrical power. Performing offline and invasive tests also add to the replacement cost. Hence, there is an increasing need to move from traditional schedule-based maintenance programs to condition-based maintenance. Mineral oils are mixtures of many different hydrocarbon molecules. They are composed essentially of saturated hydrocarbon called paraffin whose general molecular formula is C_nH_{2n+2} with n the range of 20 to 40 [1][2][3]. When use in transformers, the oil acts as a dielectric medium and also as a heat transfer agent. The breakdown of electrical insulating materials and related components inside the transformer liberates gases within the unit. The distribution of these gases can be related to the type of electrical fault, and the rate of gas generation can indicate the severity of the fault.

Insulating oils suffer from deterioration, which can become fatal for transformers. Also, discharge in oil can cause serious damage to the other insulating materials, making the monitoring of power transformers insulation an important task. When insulating oils and cellulose materials in reactive equipment are subjected to higher than normal electrical or thermal stresses, they decompose to produce certain combustible gases referred to as fault gases. For incipient fault conditions (i.e. slowly evolving fault), the gases generated will be dissolved into the oil long before any free gas is accumulated in the gas relay. Thus by analysing oil sample for dissolved gas content it is possible to assess the condition of the equipment and detecting faults at an early stage. If a fault is indicated, the type of fault can be predicted using various analysis methods.

A large number of techniques are available for transformer health monitoring. However, a focused approach is required for diagnostics. Considering the long service life of a power transformer and prevalent use of human judgment (expert), there is a need to structure a knowledge base around expert knowledge while continuing to create new diagnostic capabilities which can be plugged in. This paper gives an overview about how fusion of data mining based techniques can be used in diagnostics of power transformers.

The remaining of this paper is organized as follows. We discuss DGA in Section 2. In Section 3 we discuss about IEC. The Evolution and recent scenario in section 4.In section 5 we discuss about proposed approach. The conclusions and future directions are given in Section 6. Finally references are given.

II. DGA

Dissolved gas analysis (DGA) is the study of dissolved gases in insulating fluid such as transformer oil. Insulating materials within transformers and electrical equipment break down to liberate gases within the unit. The distribution of these gases can be related to the type of electrical fault, and the rate of gas generation can indicate the severity of the fault. The identity of the gases being generated by a particular unit can be very useful information in any preventative maintenance program.

The collection and analysis of gases in an oil-insulated transformer was discussed as early as 1928. Many years of empirical and theoretical study have gone into the analysis of transformer fault gases.

DGA usually consists of three steps: Sampling, extraction, analysis. Modern technology is changing this process with innovation of DGA units that can be transported and used on site as well as some that come directly connected to the transformer its self. Online monitoring of electrical equipment is an integral part of the smart grid. Though this new technology is promising often oil quality labs are still utilized as third party verification. Also upgrading all equipment to meet the goals of the smart grid can be cost prohibitive.

Power transformers, being key components in any electrical network, require mindful operation and maintenance, in order to obtain safe and optimum working life. As transformers age, monitoring of their condition becomes more vital, with surveillance and diagnostic techniques being needed to prevent the possibility of surprise failures. Dissolved Gas Analysis (DGA) is a fundamental technique in establishing fault mechanisms in oil-filled power transformers. In its simplest form, DGA analyzes the relative amount of three gasses in transformer oil: CH_4, C_2H_4 and C_2H_2 (methane, ethylene and acetylene) these gases are discharged from the insulation system (paper, wire) to the oil under detrimental conditions. Empirical measurements of the relative percentage of these gasses in the oil have been mapped to specific problems in the transformer.
According to Richard Green [4] the dissolved gas analysis (DGA) technique is an important tool for monitoring and troubleshooting a transformer's operational condition. There are four basic transformer fault types, categorized by severity. [5] Arching, the most severe transformer fault, produces significant amounts of hydrogen and acetylene as the mineral oil breaks down from the electrical discharge. If cellulose insulating paper is exposed to the arching, then CO_2 and CO will be generated.

Next in severity is localized heating or sparking due to intermittent high voltage flash without current. The symptomatic gases produced are increased levels of methane and ethane. Third in severity is localized overheating. Overheating, as an example, may be caused by electrical contact failure, which produces ethylene and methane gases. If severe overheating occurs, then trace amounts of acetylene may be present.

Lowest in severity is a low-energy electrical discharge that is sometimes referred to as a corona event. This low-order fault will produce hydrogen and methane with traces of ethane and ethylene. If the low-energy discharge occurs within the cellulose insulation paper, then CO_2 and CO will be present. [6]

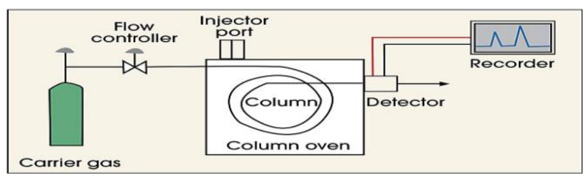


Figure 1: Basic Gas Chromatograph Components [Richard Green]

Transformer oil sample analysis is a useful, predictive, maintenance tool for determining transformer health. Along with the oil sample quality tests, performing a dissolved gas analysis (DGA) of the insulating oil is useful in evaluating transformer health. The breakdown of electrical insulating materials and related components inside a transformer generates gases within the transformer. The identity of the gases being generated can be very useful information in any preventive maintenance program. There are several techniques for detecting those gases and DGA is recognized as the most informative method.

The two principal causes of gas formation within an operating transformer are electrical disturbances and thermal decomposition. All transformers generate gases to some extent at normal operating temperatures. Insulating mineral oils for transformers are mixtures of many different hydrocarbon molecules, and the decomposition processes for these hydrocarbons in thermal or electrical faults are complex. The fundamental chemical reactions involve the breaking of carbon hydrogen and carbon-carbon bonds. During this process, active hydrogen atoms and hydrocarbon fragments are formed. These fragments can combine with each other to form gases: hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_4), and ethane (C_2H_6).

Further, when cellulose insulation is involved, thermal decomposition or electric faults produce methane (CH_4), hydrogen (H_2), carbon monoxide (CO), and carbon dioxide (CO_2). The gases listed above are generally referred to as key gases.

The gases listed above are considered key gases and are generally considered combustible. The total of all combustible gases may indicate the existence of any one or a combination of thermal, electrical, or corona faults.

III. IEC Ratio Method

Like a doctor perform different test for the disease, DGA can warn about the problem or fault in oil. It diagnosis and increases the chances of finding the appropriate cure. The detection of incipient faults in oil immersed transformers by examination of gases dissolved in oil, developed from original Buchholz relay application. According to N. A. Muhamad et al. [7] Gas Chromatograph (GC) is the most practical method available to identify combustible gases. GC involves both a qualitative and quantitative analysis of gases dissolved in transformer oil [8].

According to N. A. Muhamad et al. [7] there are several approaches which are used for DGA. Some among them are Norms Method, Gas Ratio Method and Key Gas method. In condition monitoring, the advantage of using ratio method is that, they overcome the issue of volume of oil in the transformer by looking into the ratio of gas pairs rather than absolute values.

Rogers Ratio Method of DGA [9] is an additional tool that may be used to look at dissolved gases in transformer oil. Rogers Ratio Method compares quantities of different key gases by dividing one into the other. This gives a ratio of the amount of one key gas to another. By looking at the Gas Generation Chart, you can see that, at certain temperatures, one gas will be generated more than another gas. Rogers used these relationships and determined that if a certain ratio existed, then a specific temperature had been reached. By comparing a large number of transformers with similar gas ratios and data found when the transformers were examined, Rogers could then say that certain faults were present. Like the Key Gas Analysis above, this method is not a "sure thing" and is only an additional tool to use in analyzing transformer problems. Rogers Ratio Method, using three-key gas ratios, is based on earlier work by Dorneneburg, who used four gas ratios. Ratio methods are only valid if a significant amount of the gases used in the ratio is present.

When a fault occurs inside a transformer, there is no problem with minimum gas amounts at which the ratio are valid. There will be more than enough gas present. The Roger's method utilizes four gas ratios: CH_4/H_2, C_2H_6/CH_4, C_2H_4/C_2H_6 and C_2H_2/C_2H_4. These ratios and the resultant fault indications are based on large numbers of DGAs and transformer failures and what was discovered after the failures. Rogers's ratio method as presented in Table 1(a,b,c).IEC uses 3 gas ratios, C_2H_2/C_2H_4, CH_4/H_2 and C_2H_4/C_2H_6. Each ratio is quantized to a classification code 0, 1, or 2. So in total there is to be 27 possible combinations (fault types) but IEC 599 defines only 11 combinations leading to non-decision diagnosis, when falling within the invalid group of 16 remaining combinations. In [1, 10], IEC codes are extended into expert rules using experiences in the field by filling in the gaps created by IEC. The IEC Ratio codes and Fault types are given in Table 2 and Table 3 respectively. The main advantage is elimination of the non-decision problem with all the 27 combinations included. The IEC codes are extended into the expert rules using experiences in the field by filling in the gaps created by IEC. The result according to IEC method is shown in Table4.

Table 1(a): Roger's Ratio Codes [3]

Gas Ratio	Ratio Codes
CH_4/H_2	i
$C2H_6/CH_4$	j
C_2H_4/C_2H_6	k
C_2H_2/C_2H_4	l

Table 1(b): Fault Codes of Rogers Ratio [3]

Ratio Code	Range	Code
i	<0.1 >0.1,<1.0 >=1.0,<3.0 >=3.0	5 0 1 2
j	<1.0	0

	>=1.0	1
k	<1.0 >=1.0,<3.0 >=3.0	0 1 2
l	<0.5 >=0.5,<3.0 >=3.0	0 1 2

Table 1(c): Classification based on Roger's Ratio Codes [3]

i	j	k	l	Diagnosis
0	0	0	0	Normal Deterioration
5	0	0	0	Partial Discharge
1-2	0	0	0	Slight Overheating <150 ^{0} C
1-2	1	0	0	Overheating 150 ^{0} C – 200 ^{0} C
0	1	0	0	Overheating 200 ^{0} C – 300 ^{0} C
0	0	1	0	General Conductor Overheating
1	0	1	0	Winding Circulating Current
1	0	2	0	Core and Tank circulating currents, Overhead Joints
0	0	0	1	Flashover without power follow through
0	0	1-2	1-2	Arc with Power follow through
0	0	2	2	Continuous Sparking to floating Potential
5	0	0	1-2	Partial discharge with tracking

Table 2: IEC Ratio Codes [11]

Ranges of the Gas Ratio	Codes of Different Gas Ratio		
	C_2H_2\C2H4	CH_4\H_2	C_2H_4\C_2H_6
<0.1	0	1	0
0.1-1	1	0	0
1-3	1	2	1
>3	2	2	2

Table 3: Fault types according to the IEC Gas Ratio Codes [11]

Fault Type Number	Fault Type	C_2H_2/ C_2H_4	CH_4/ H_2	C_2H_4/ C_2H_6
1	No Fault	0	0	0
2	<150 ^{0}C Thermal Fault	0	0	1
3	150^{0}C-300^{0}C Thermal Fault	0	2	0
4	300^{0}C -700^{0}C Thermal Fault	0	2	1
5	>700 ^{0}C Thermal Fault	0	2	2
6	Low Energy PD	0	1	0
7	High Energy PD	1	1	0
8	Low Energy Discharge	1 or 2	0	1 or 2
9	High Energy Discharge	1	0	2

Table 4: DGA Sample Data with IEC Method

S.NO	H_2	CH_4	C_2H_4	C_2H_6	C_2H_2	FAULT CODE	FAULT TYPE
1	4.5925	24.797	13.8563	14.707	.003033	3	150^0C-300^0C Thermal Fault
2	5.3862	.4166	.028271	.04776	.000408	6	Low Energy PD
3	1.6427	1.4899	.5277	7.4315	.00452	1	No fault
4	4.1159	.8980	2.5779	.9623	.03779	2	<150 ^{0}C Thermal Fault
5	1.7011	1.1971	.8177	.117	.1293	9	High Energy Discharge
6	1.8589	3.108	3.212	2.148	.00807	4	300^0C -700^0C Thermal Fault
7	.3985	5.5257	4.442	.8250	.00277	5	>700 ^{0}C Thermal Fault
8	1.3229	.4296	.04557	.000205	.01314	9	High Energy Discharge
9	29.9914	1.8591	.5192	.7374	.05910	7	High Energy PD
10	4.4171	.3517	.1288	.0297	.005011	-	Null
11	1.7020	.2414	.2545	.2089	.00405	2	<150 ^{0}C Thermal Fault
12	6.0646	12.025	15.713	.6513	.001383	5	>700 ^{0}C Thermal Fault
13	.7323	3.0435	1.382	.2912	.00198	5	>700 ^{0}C Thermal Fault
14	2.7011	1.1871	.7167	.217	.2293	9	High Energy Discharge
15	.1487	.9906	.1008	.0745	.00965	4	300^0C -700^0C Thermal Fault
16	6.8729	2.2421	.1700	.4064	.00599	1	No Fault
17	30.991	2.8591	.6192	.6374	.06910	7	High Energy PD
18	2.6080	18.9712	2.7400	39.848	.00415	3	150^0C-300^0C Thermal Fault
19	4.3368	1.0566	.9231	.2002	.002501	8	Low Energy Discharge
20	5.7787	.5458	.07298	.1546	.00692	6	Low Energy PD
21	8.6976	1.0636	2.1259	.5134	.5348	9	High Energy Discharge
22	3.1681	9.265	6.6307	2.9401	.02215	4	300^0C -700^0C Thermal Fault
23	1.8012	1.231	.6167	.113	.2133	9	High Energy Discharge
24	.7683	.7255	.00873	.1139	.00994	-	Null
25	2.545	.1450	.0044	.00074	.01355	-	Null
26	1.8421	.8287	.1761	.6180	.00252	1	No fault
27	.8573	6.3671	4.9939	5.0809	.000120	3	150^0C-300^0C Thermal Fault
28	4.4798	45.47	342.5	35.39	21.562	5	>700 ^{0}C Thermal Fault
29	31.9914	2.113	.5583	.6613	.0513	6	Low Energy PD
30	7.3779	.6711	.09027	.06864	.003792	-	Null
31	.5585	.1546	.0041	.000846	.01696	8	Low Energy Discharge
32	7.9165	4.3174	5.211	3.284	1.8652	8	Low Energy Discharge

But, the drawback of these ratio methods is that it fails to cover all range of data and quite fall outside the scope of tables. To overcome this problem, in this paper we use data mining with IEC ratio is used to overcome the drawback and combine both codes.

IV. Evolution and Recent Scenario

In 2008, Dr. D.V.S.S. Siva Sarma et al. [12] discuss Non-Destructive Evaluation of Power transformer by monitoring various parameters, to predict its in-service behaviour, is very much necessary for operating engineer to avoid catastrophic failures and costly outages. Dissolved Gas Analysis (DGA) is an important tool for transformer fault diagnosis. The ratio methods used in the DGA have an advantage that they are independent of volume of gases involved. But the main drawback of the ratio methods is that they fail to cover all ranges of data and ambiguity about the boundaries of gas ratios in diagnosing the fault. Artificial Intelligence techniques like Artificial Neural Network (ANN), Fuzzy Logic (FL) and Extension Neural Network (ENN) are used to overcome the above drawbacks, and the results of various methods are compared in their research.

In 2008, Zhang Wei-zheng et al. [13] about the Fisher rule to evaluate the results of the two pre-treatment methods is also introduced. The evaluation of the results indicates that both of the two data pre-treatment methods can achieve the purpose of big difference in the value of mean between classes and small difference in dispersion of a class. The DGA data of the failure transformers are treated by different normalization methods as the training samples, and then the samples are trained in the compound neural networks which use the CP algorithm. The diagnosis results of the test samples indicate that the new methods may help to improve the precision of network diagnosis.

In 2009, C.K. Diwedi et al. [14] discusses from the test results, it is observed that the transformer which has very good result. Winding cellulose paper may be aged to such an extent (assessed from DP) that may sudden force or transient may result in failure. DP cannot be conducted regularly to ascertain mechanical integrity of the winding paper. FURAN analysis is a substitute for DP. But most of time, Furans are not detected and there is no universal correlation available for DP and Furan.. Both, the moisture content and ageing of paper influences furan. Frequency response analysis gives the information regarding the movement of winding but does not give much, information above mechanical integrity of winding which is essential for transformer reliability. They proposed, an approach has been made to compare the moisture content in the winding from RVM and estimated from oil ppm (using Norris diagram) and estimated from winding DLA.

In 2009, Z. Yang et al. [10] present a novel association rule mining (ARM)-based dissolved gas analysis (DGA) approach to fault diagnosis (FD) of power transformers. In the development of the ARM-based DGA approach, an attribute selection method and a continuous datum attribute discretization method are used for choosing user-interested ARM attributes from a DGA data set, i.e. the items that are employed to extract association rules. The given DGA data set is composed of two parts, i.e. training and tests DGA data sets. An ARM algorithm namely Apriori-Total from Partial is proposed for generating an association rule set (ARS) from the training DGA data set. Afterwards, an ARS simplification method and a rule fitness evaluation method are utilized to select useful rules from the ARS and assign a fitness value to each of the useful rules, respectively. Based upon the useful association rules, a transformer FD classifier is developed, in which an optimal rule selection method is employed for selecting the most accurate rule from the classifier for diagnosing a test DGA record. For comparison purposes, five widely used FD methods are also tested with the same training and test data sets in experiments. Results show that the proposed ARM-based DGA approach is capable of generating a number of meaningful association rules, which can also cover the empirical rules defined in industry standards.

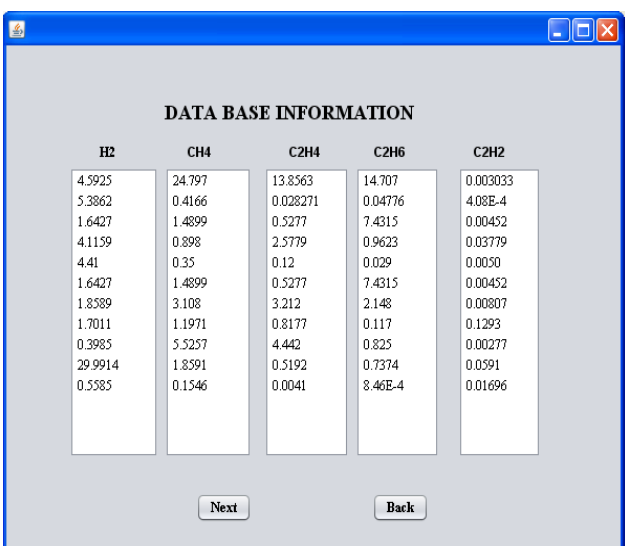
In 2010, Bálint Németh et al. [15] deal with an expert system that utilizes fuzzy logic implementation into dissolved gas in oil analysis technique. To improve the diagnosis accuracy of the conventional dissolved gas analysis (DGA) approaches, this part proposes a fuzzy system development technique based 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. Then they deals with 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 systems also consider other information of transformer such as type, voltage level, maintenance history, with or without tap changer etc. These proposed approaches provide the user a more accurate result and better condition awareness of the transformer.

V. Proposed Approach (IEC + Association)

Our approach is based on IEC ratio method where we can find the fault efficiently and accurately. Our proposed algorithm is shown below:

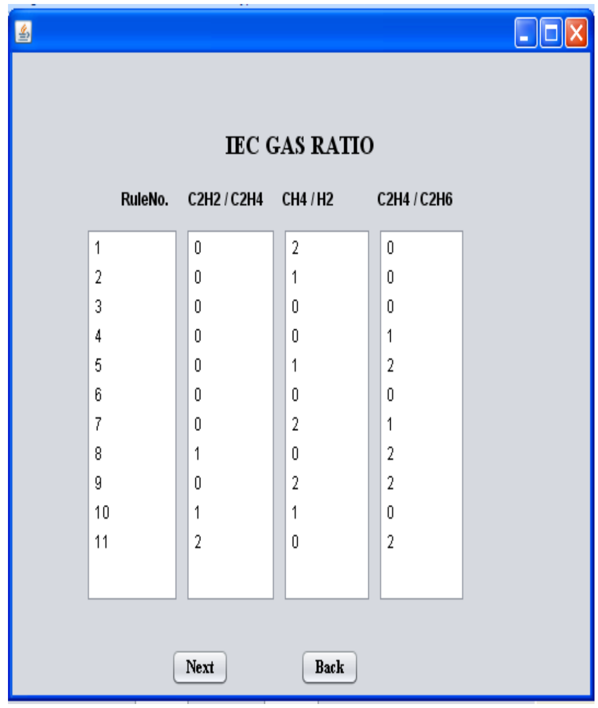
1. Insert the ratio of H_2, CH_4, C_2H_4, C_2H_6 and C_2H_2.[Figure 2]
2. Generate Gas Ratio Rule which is CH4/H2, C_2H_2/C_2H_4, and C_2H_4/C_2H_6. IEC Ratio Method Uses the Following Three Ratios: CH_4/H_2, C_2H_2/C_2H_4, and C_2H_4/C_2H_6. [Figure 3]
3. Find the Fault according to the condition given in table 2 and table 3.[Figure 4]
4. Apply association Rules:
    4.1 Pattern is generated.
    4.2 All itemsets that have support above the user specified minimum support are generated. These itemset are called the large itemsets. All others are said to be small.
    4.3 For each large item set, all the rules that have minimum confidence are generated as follows: for a large item set X and any Y C X, if support(X)/support(X - Y) 2 minimum- confidence, then the rule X - Y j Y is a valid rule.
    4.4 Enter the minimum support.
    4.5 Match the database which satisfies the minimum support.

5. Print the fault type.



H2	CH4	C2H4	C2H6	C2H2
4.5925	24.797	13.8563	14.707	0.003033
5.3862	0.4166	0.028271	0.04776	4.08E-4
1.6427	1.4899	0.5277	7.4315	0.00452
4.1159	0.898	2.5779	0.9623	0.03779
4.41	0.35	0.12	0.029	0.0050
1.6427	1.4899	0.5277	7.4315	0.00452
1.8589	3.108	3.212	2.148	0.00807
1.7011	1.1971	0.8177	0.117	0.1293
0.3985	5.5257	4.442	0.825	0.00277
29.9914	1.8591	0.5192	0.7374	0.0591
0.5585	0.1546	0.0041	8.46E-4	0.01696

Figure 2: Sample Database



RuleNo.	C2H2 / C2H4	CH4 / H2	C2H4 / C2H6
1	0	2	0
2	0	1	0
3	0	0	0
4	0	0	1
5	0	1	2
6	0	0	0
7	0	2	1
8	1	0	2
9	0	2	2
10	1	1	0
11	2	0	2

Figure 3: IEC Gas Ratio

Our approach find all most all type of faults according to the fault type which are in accordance of IEC table with the help of association rule mining. According to Sotiris Kotsiantis et al. [16] Association rule mining is one of the most important and well researched techniques of data mining, was first introduced in [17]. It aims to extract interesting correlations,frequent patterns, associations or casual structures among sets of items in the transaction databases or other data repositories. Association rules are widely used in various areas such as telecommunication networks, market and risk management, inventory control etc. Various association mining techniques and algorithms will be briefly introduced and compared later. Association rule mining is to find out association rules that satisfy the predefined minimum support and confidence from a given database. The problem[16] is usually decomposed into two subproblems. One is to find those itemsets whose occurrences exceed a predefined threshold in the database; those itemsets are called frequent or large itemsets. The second problem is to generate association rules from those large itemsets with the constraints of minimal confidence. Suppose one of the large itemsets is Lk, Lk = {I1, I2, … , Ik}, association rules with this itemsets are generated in the following way: the first rule is {I1, I2, … , Ik-1}⇒ {Ik}, by checking the confidence this rule can be determined as interesting or not. Then other rule are generated by deleting the last items in the antecedent and inserting it to the consequent, further the confidences of the new rules are checked to determine the interestingness of them. Those processes iterated until the antecedent becomes empty. Since the second subproblem is quite straight forward, most of the researches focus on the first subproblem.

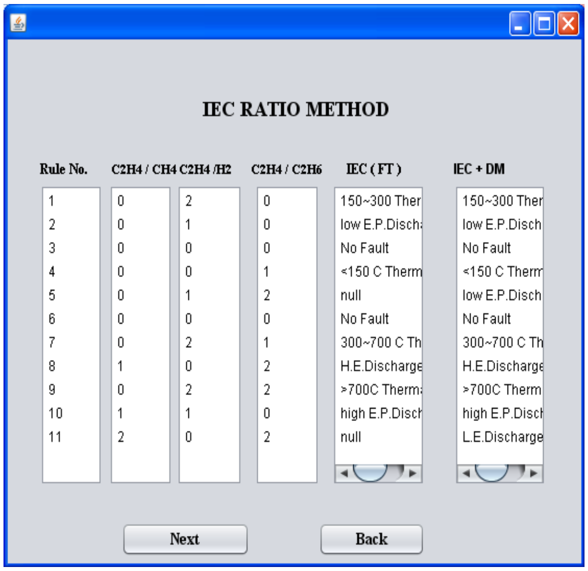


Figure 4: Fault Type

IEC + DM approach is work in the following manner.

1) If the pattern is found from the IEC method the fault is returned according to the IEC method.
2) If the pattern is not found then we choose the minimum associated rule from the IEC Rule table.
3) Because we associate related Items, this approach provides a good and efficient way of finding faults.

The sample for this study and analysis is taken from Office of the Executive Engineer; Testing Division The sample for this study and analysis is taken from Office 0f the Executive Engineer, Testing Division II, MPPTCL Nayagaon Jabalpur, Oil Testing Laboratory.

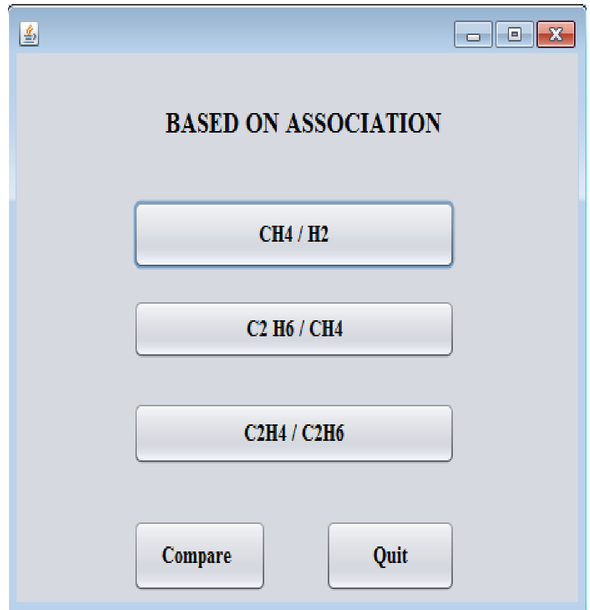


Figure 5: Based on Association

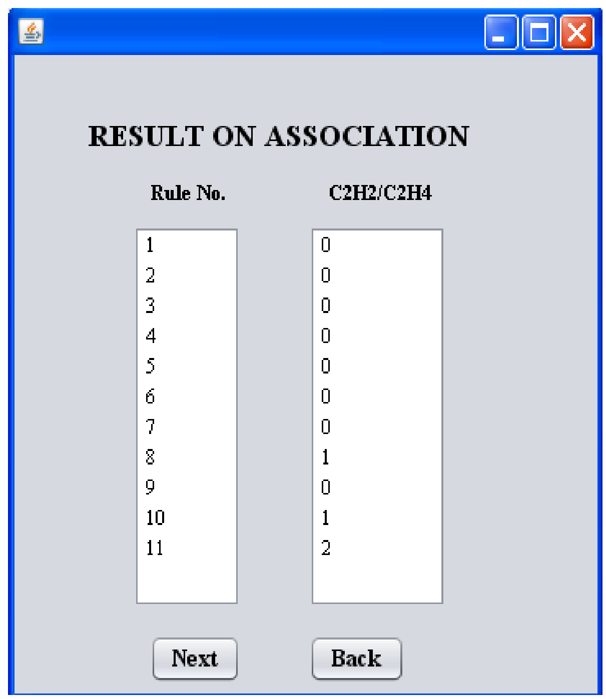


Figure 6: Result Based on Association

Table 5: Result Based on IEC + DM

S.NO	IEC (FT)	IEC + DM
1	150^{0}C-300^{0}C Thermal Fault	150^{0}C-300^{0}C Thermal Fault
2	Low Energy PD	Low Energy PD
3	No fault	No fault
4	<150 ^{0}C Thermal Fault	<150 ^{0}C Thermal Fault
5	High Energy Discharge	High Energy Discharge
6	300^{0}C -700^{0}C Thermal Fault	300^{0}C -700^{0}C Thermal Fault
7	>700 ^{0}C Thermal Fault	>700 ^{0}C Thermal Fault
8	High Energy Discharge	High Energy Discharge
9	High Energy PD	High Energy PD
10	Null	Low Energy PD
11	<150 ^{0}C Thermal Fault	<150 ^{0}C Thermal Fault
12	>700 ^{0}C Thermal Fault	>700 ^{0}C Thermal Fault
13	>700 ^{0}C Thermal Fault	>700 ^{0}C Thermal Fault
14	High Energy Discharge	High Energy Discharge
15	300^{0}C -700^{0}C Thermal Fault	300^{0}C -700^{0}C Thermal Fault
16	No Fault	No Fault
17	High Energy PD	High Energy PD
18	150^{0}C-300^{0}C Thermal Fault	150^{0}C-300^{0}C Thermal Fault
19	Null	No fault
20	Low Energy PD	Low Energy PD
21	High Energy Discharge	High Energy Discharge
22	300^{0}C -700^{0}C Thermal Fault	300^{0}C -700^{0}C Thermal Fault
23	High Energy Discharge	High Energy Discharge
24	Null	High Energy Discharge
25	Null	Null
26	No fault	No fault
27	150^{0}C-300^{0}C Thermal Fault	150^{0}C-300^{0}C Thermal Fault
28	>700 ^{0}C Thermal Fault	>700 ^{0}C Thermal Fault
29	Low Energy PD	Low Energy PD
30	Null	Low Energy PD
31	Null	Low Energy Discharge
32	Null	High Energy Discharge

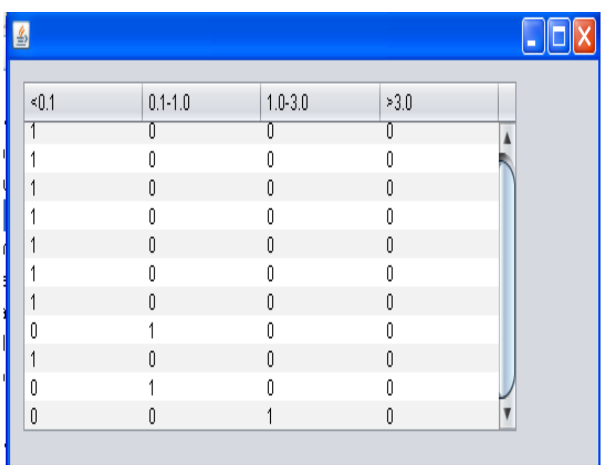


Figure 7: Occurences Count

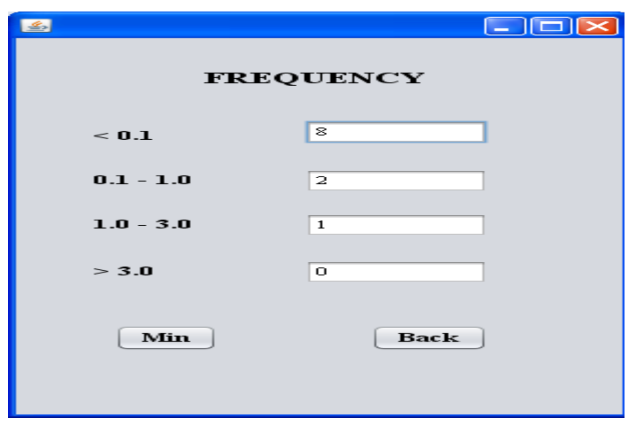


Figure 8: Frquency

Then we enter the minimum support value 2.

Figure 9: Result Set

Our comparison shows the fault percentage of each ratio which is shown in figure 10.

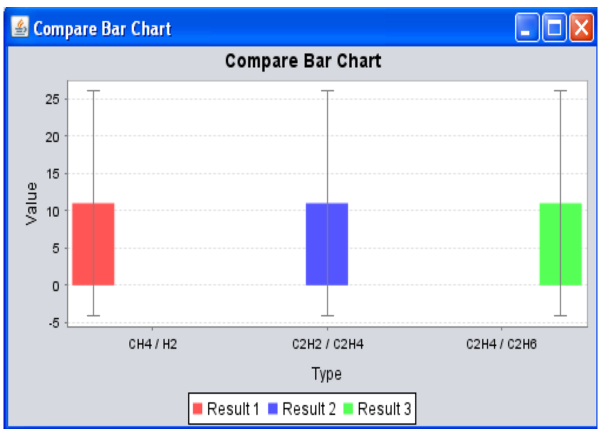


Figure 10: Comparison

VI. Conclusion and Future Directions

The main procedures of our approach are developed, including data pre-processing, rule discovery with Association Rule Mining (ACM). Then, with the useful rules extracted from a generated ACM, a classifier is constructed and utilized of power transformers with the proposed implementation method. For comparison purposes, we can input set of ratio using IEC approach. In our approach we can provide single and multilevel classification, based on that our fault analysis is approx. on scale of 1/1.

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