Evidential Reasoning In Dissolved Gas Analysis For Power Transformers

K. Spurgeon, W.H. Tang, Q.H. Wu, *Senior Member IEEE*, Z.J. Richardson, G. Moss

***Abstract*--This paper describes how the information combination capabilities of *Evidential Reasoning* (ER) can be harnessed to combine decisions made by subsystems simply by treating each decision as a piece of evidence. The example of *Dissolved Gas Analysis* (DGA) for transformers is used as a case in point to demonstrate the effectiveness of ER. Several traditional DGA methods are refined using *Fuzzy Set Theory* techniques to soften their crisp decision boundaries, therefore giving the methods the power to generate probabilities of faults. These *refined* methods are then used to process raw DGA data. The combined results using ER are a set of possible fault types and an associated probability for each.**

***Index Terms*--Evidential reasoning, fuzzy set theory, dissolved gas analysis.**

I. INTRODUCTION

EVIDENTIAL Reasoning (ER) is an approach that was created for the purpose of evaluating Multiple-Attribute Decision Making (MADM) problems that have both quantitative and qualitative attributes (Yang *et al*. 1994-1), more commonly known as hybrid MADM problems. There are many examples of hybrid MADM problems in industry and other real-world situations, some of which have very different natures. The concept stage of design in engineering is such a case (Yang *et al*. 1997), as is the evaluation of teacher performance in higher education. When deciding between several alternatives or comparing performance, many comparative sub-decisions need to be made. To make the final decision each alternative must be ranked by considering all relevant information. For the decision making between concept designs of engineering products, both the technical and economical performance must be considered. All this information is measured with either raw numerical values or subjective judgements drawn from prior experiences (knowledge). In the case of the teacher performance ranking problem each facet of a teacher's performance must be evaluated, e.g. quantitative information such as student examination results must be combined with subjective judgments regarding their method and attitude. In both cases as with virtually all real decision problems, we require the elicitation of subjective judgements. However, subjective judgements such as these often hold uncertainties in their evaluation of an attribute.

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Yang (Yang *et al*. 1994-1, Yang *et al*. 1994-2) suggests that the simplest way to evaluate the state of a qualitative attribute is to define a series of evaluation grades which can then be quantified using a numerical scale. The designer must also consider how accurately the subjective judgement can be made by choosing the number of evaluation grades, so to avoid too narrow decision boundaries whilst still maintaining a high enough accuracy. For example, when evaluating the paint finish of a motorcycle only 3 or 4 grades would be necessary, i.e. [Poor, Average, Good, Excellent], any more and the task would become too complex and too dependent upon the evaluator. In traditional probability theories, any belief not assigned to a hypothesis *H* is assigned to the complement of that hypothesis *comp(H)*. In contrast, Dempster-Schaffer Theory uses basic probability assignments. It is required that given a piece of evidence, the commitment of belief in that hypothesis does not necessarily mean that the remaining belief must be assigned to the compliment of the hypothesis, but to the whole sample space, which in our case is the evaluation grade.

In our test case of Dissolved Gas Analysis (DGA) the results from the traditional methods are known to be fraught with uncertainties due to the assumptions and generalisations upon which each method is founded. However, DGA engineers constantly outperform these methods in their diagnoses by using several diagnosis methods, plus their expertise and judgement to predict what is really going on inside the power transformer of interest. We postulate that by treating each result from various DGA diagnosis methods as a piece of evidence pertaining to the condition of the transformer, such results can be combined using ER to provide the most balanced overall decision.

II. TRADITIONAL DGA METHODS WITH FUZZY LOGIC BOUNDARIES

The three traditional DGA methods incorporated in this study are (*i*) Roger's Ratio Method (RRM), (*ii*) Dornenburg's Ratio Method (DRM) and (*iii*) the Key Gas Method (KGM).

The fingerprint gases used by all the three methods to be harnessed are Carbon Monoxide (CO), Hydrogen (H_2), Methane (CH_4), Ethane (C_2H_6), Ethylene (C_2H_4) and Acetylene (C_2H_2). The ratios for DGA diagnosis are defined as: $R_1 = CH_4/H_2$, $R_2 = C_2H_2/C_2H_4$, $R_3 = C_2H_2/CH_4$, $R_4 = C_2H_6/C_2H_2$ and $R_5 = C_2H_4/C_2H_6$. Conventionally, all the above DGA techniques make decisions based on the crisp values of the ratios they use. In this study, fuzzy membership functions are used by the above ratio methods to soften the decision boundaries, which are briefly introduced in this section.

A. Roger's Ratio Method

Roger's Ratio Method is presented in Table I, and the ratios employed for diagnosis are derived from various combinations of the fingerprint gases (Mollmann *et al*. 1999).

Fault	R_1	R_2	R_5
No Fault	> 0.1 and < 1.0	< 0.1	< 1.0
PD	< 0.1	< 0.1	> 1.0 and < 1.0
Arcing	0.1 − 1.0	0.1 − 3.0	> 3.0
Low Temp. Thermal	< 0.1	> 0.1 and < 1.0	> 1.0 and < 3.0
Thermal < 700°C	> 1.0	< 0.1	1.0 − 3.0
Thermal > 700°C	< 0.1	> 1.0	> 3.0

Table I Roger's Ratio Method

B. Dornenburg's Ratio Method

For Dornenburg's Ratio Method, the fingerprint gas ratios are compared with some predetermined values to determine the types and levels of faults. The relationships between fault types and the applied ratios are listed in Tables II and III.

Fault	R_1	R_2	R_3	R_4
Thermal	> 1.0	< 0.75	< 0.3	> 0.4
PD	< 0.1	N/A	< 0.3	> 0.4
Arcing	> 0.1 and < 1.0	> 0.75	> 0.3	< 0.4

Table II Dornenburg's Ratio Method

Gas	H_2	CH_4	CO	C_2H_2	C_2H_4	C_2H_6
L1 (ppm)	100	120	350	35	50	65

Table III Dornenburg's L1 Limits

C. The Key Gas Method

The Key Gas Method simply utilises relative percentages of the selected fingerprint gases to identify fault types. This method actually uses four characteristic charts which represent typical relative gas concentrations for four general fault types, i.e. OverHeating of Cellulose (*OHC*), OverHeating of Oil (*OHO*), Partial Discharge (*PD*) or *Arcing*. The relationships between fault types and key gas percentages are listed in Table IV.

Fault	CO	H_2	CH_4	C_2H_6	C_2H_4	C_2H_2
OHO	N/A	2	16	19	63	N/A
OHC	93	N/A	N/A	N/A	N/A	N/A
PD	N/A	85	13	1	1	N/A
Arcing	N/A	60	5	2	3	30

Table IV Key Gas Method

D. Fuzzy Logic Boundaries

To calculate the percentage support given by each ratio method to each fault type, we introduce fuzzy logic boundaries to replace the crisp decision boundaries employed by each method. The yes or no decision for each fault can be converted into a level of association, i.e. a closeness of the data to fault conditions, which represents a probability of fault. Since the crisp decision boundaries take on the form of step boundaries, they can be easily converted to fuzzy equivalents using appropriate sigmoid functions and Gaussian bell functions of the forms shown in equations (1) and (2) respectively.

$$f(x) = (1 + e^{-(ax+c)})^{-1} \qquad (1)$$

$$f(x) = e^{((x-c)/a)^{2b}} \qquad (2)$$

where a, b and c are the parameters of the above fuzzy membership functions, which are derived from international standards. It must be noted that the choice of the parameters used in these equations is trivial and not relevant to this paper.

III. Development and Implementation of New Approach Under ER Framework

ER requires that a set of common hypotheses be used for all sources of information H,

$$H = \{H_1, \ldots, H_n, \ldots, H_N\} \qquad n = 1, \ldots, N \qquad (3)$$

where N is the number of hypotheses. From Tables I, II and IV it can be seen that the minimum exhaustive set of fault types is as follows.

$$H = \{OHC, Thermal, PD, Arcing\} \qquad (4)$$

The decision making process of DGA is essentially a tree structure comprising three levels, i.e. the first level represents the raw DGA data; the second level is composed of three DGA methods processing the data; and the third level is the ER algorithm combining the results from the second level. The ER tree shown in Fig. 1 represents the decision making process for DGA.

Using the notation designed by Yang (Yang *et al*. 1994-2), (and noting that the standard k suffix will be ignored), a number of composite and basic factors are derived as follows. A set of composite factors $f = \{f_1, f_2, f_3\}$ which are the diagnoses made by each of the DGA methods is defined, as well as the basic factors which can be grouped into three subsets as below.

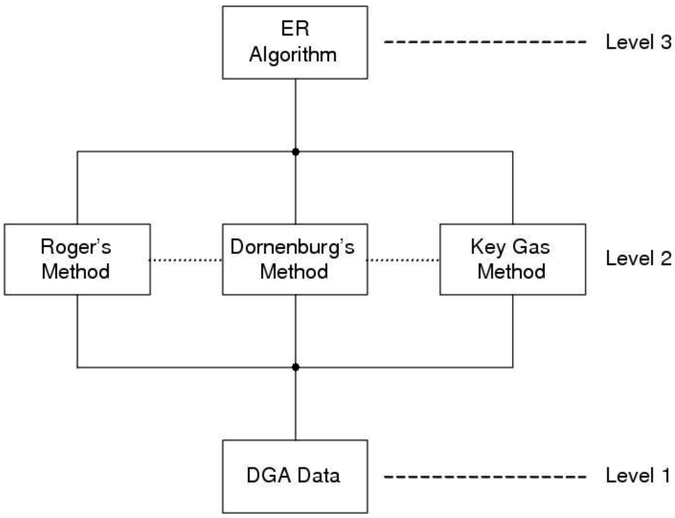

Figure 1 ER Tree Representing Decision Process

$e = \{e_{RRM}, e_{DRM}, e_{KGM}\} = \{e_1, e_2, e_3\}$

where

$e_{RRM} = \{LowTemp., Thermal < 700^oC, Thermal > 700^oC, PD, Arcing\}$
$= \{e^1_1, e^2_1, e^3_1, e^4_1, e^5_1\}$
$e_{DRM} = \{Thermal, PD, Arcing\}$
$= \{e^1_2, e^2_2, e^3_2\}$
$e_{KGM} = \{OHC, Thermal, PD, Arcing\}$
$= \{e^1_3, e^2_3, e^3_3, e^4_3\}$

We can also define a set $L = \{L_1, L_2, L_3\}$, where L_j ($j = 1,\dots,3$) denotes the number of basic factors contributing to the evaluation of the composite factor f_j, i.e. $L = \{5,3,4\}$.

In the decision tree defined above, all three evaluation tools are equally important, therefore the relative weights of each composite factor (ζ) are assigned as 1, i.e. $\zeta = \{\zeta^1_1, \dots, \zeta^i_j, \dots, \zeta^4_3\} = \{1,1,\dots,1,1\}$ ($1 \le i \le L_j$). This means that the normalised relative weights $\bar{\zeta}$ are also unity. Since we can say that if the most important method predicts 100% failure we want a 100% failure result, then we can also set α, the "significance" factor, to be one. This then allows $\beta_{Hn}(e^i_j)$, the belief with which factor e^i_j supports the evaluation of the transformer's condition to H_n, to be directly equal to $m^n_{j,i}$. $m^n_{j,i}$ denotes the basic probability assignment that the transformer's condition will be evaluated to grade H_n given e^i_j. With the above ER procedures, the probability assignments for each basic factor are determined, which are listed in Tables V, VI and VII respectively.

By defining a factor subset $e_{Ij(i)} = \{ e^1_j,\dots,e^i_j\}$, $1 \le i \le L_j$, we can also define a combined probability assignment $m^{\Psi}_{I_j(i)}$. $m^{\Psi}_{I_j(i)}$ is the probability that the transformer's condition will be evaluated to Ψ $(\Psi \subseteq H)$, given the factor subset $e_{Ij(i)}$. Any remaining belief is noted as $m^H_{j,i}$, that is $m^H_{j,i} = 1 - \sum_{n=1}^{N} m^n_{j,i}$. Noticing that $e_{Ij(1)} = e^1_j$, the following general algorithm is utilised to combine the evidence presented at the basic factor level.

	H_1	H_2	H_3	H_4
e^1_1	0	$m^2_{1,1}$	0	0
e^2_1	0	$m^2_{1,2}$	0	0
e^3_1	0	$m^2_{1,3}$	0	0
e^4_1	0	0	$m^3_{1,4}$	0
e^5_1	0	0	0	$m^4_{1,5}$

Table V Probability Assignments for f_1

	H_1	H_2	H_3	H_4
e^1_2	0	$m^2_{2,1}$	0	0
e^2_2	0	0	$m^3_{2,2}$	0
e^3_2	0	0	0	$m^4_{2,3}$

Table VI Probability Assignments for f_2

	H_1	H_2	H_3	H_4
e^1_3	$m^1_{3,1}$	0	0	0
e^2_3	0	$m^2_{3,2}$	0	0
e^3_3	0	0	$m^3_{3,3}$	0
e^4_3	0	0	0	$m^4_{3,4}$

Table VII Probability Assignments for f_3

For $j = 1,2,\dots,3$ and $i = 1,2,\dots,L_j-1$:

$$\{H_n\}: m^n_{I_j(i+1)} = K_{I_j(i+1)}(m^n_{I_j(i)}m^n_{j,i+1} + m^n_{I_j(i)}m^H_{j,i+1} + m^H_{I_j(i)}m^n_{j,i+1}), \quad n = 1,\dots,N \quad (5)$$

$$\{H\}: m^H_{I_j(i+1)} = K_{I_j(i+1)}m^H_{I_j(i)}m^H_{j,i+1}), \quad (6)$$

$$K_{I_j(i+1)} = \left[1 - \sum_{\tau=1}^{N}\sum_{\rho=1,\rho\ne\tau}^{N} m^{\tau}_{I_j(i)}m^{\rho}_{j,i+1}\right], \quad (7)$$

If we now let $m^n_{I_j(L_j)} = m^n_j$, then the intermediate evaluation Table VIII is generated.

If we define a composite factor subset $f_{I(i)} = \{f_1,\dots,f_i\}$, then the probabilities in Table VIII can be combined using a simpler form of the ER algorithm as described in equations (8-10).

For i=1,2:

	H_1	H_2	H_3	H_4
f_1	$m^1{}_1$	$m^2{}_1$	$m^3{}_1$	$m^4{}_1$
f_2	$m^1{}_2$	$m^2{}_2$	$m^3{}_2$	$m^4{}_2$
f_3	$m^1{}_3$	$m^2{}_3$	$m^3{}_3$	$m^4{}_3$

Table VIII Intermediate Evaluation Table

$$\{H_n\}: m^n_{I(i+1)} = K_{I(i+1)}(m^n_{I(i)}m^n_{i+1} + m^n_{I(i)}m^H_{i+1} + m^H_{I(i)}m^n_{i+1}), \quad n = 1,...,N \qquad (8)$$

$$\{H\}: m^H_{I(i+1)} = K_{I(i+1)}m^H_{I(i)}m^H_{i+1}), \qquad (9)$$

$$K_{I(i+1)} = \left[1 - \sum_{\tau=1}^{N}\sum_{\rho=1,\rho\neq\tau}^{N} m^\tau_{I(i)}m^\rho_{i+1}\right], \qquad (10)$$

We are now presented with an overall evaluation of the transformer's condition, based upon the evidence provided by the traditional DGA methods illustrated in Section II.

IV. Test and Results

Using the typical DGA data in Table IX[1], the new DRM implementing suitable fuzzy functions produces the following results:

Gas	H_2	CH_4	CO	C_2H_2	C_2H_4	C_2H_6
ppm	270	190	280	37	17	4

Table IX Typical DGA Data

- R_1 provided 92.7% support for a thermal fault, i.e.
  $Pr(Thermal|R_1)_{DRM} = 0.9270$
  $Pr(Thermal|R_2)_{DRM} = 0.0790$
  $Pr(Thermal|R_3)_{DRM} = 0.9988$
  $Pr(Thermal|R_4)_{DRM} = 0.5000$

which gives a support of 62.62% for the *Thermal* Fault condition by averaging the above values (since each is equally important in the decision making). Similarly, support for *PD* Fault is 41.31% and support for *Arcing* Fault equals 73.13%.

Combining these using equations (8-10) provides us the following result:

- Overall evaluation using ER[2] = [0, 0.235, 0.434, 0.114]

Using the same techniques, the results in Tables X, XI and XII are made by the three traditional DGA methods, i.e. conditional probabilities for Roger's Ratio Method, conditional probabilities for Dornenburg's Ratio Method and conditional probabilities for Key Gas Method.

[1] This test data and matching diagnosis are taken directly from NGT's DGA database.
[2] The zero represents the probability of *OHC* since *DRM* cannot determine this fault.

	H_1	H_2	H_3	H_4
$e^1{}_1$	0	0.3287	0	0
$e^2{}_1$	0	0.1072	0	0
$e^3{}_1$	0	0.1072	0	0
$e^4{}_1$	0	0	0.3438	0
$e^5{}_1$	0	0	0	0.3228

Table X Conditional Probabilities for Roger's Ratio Method

	H_1	H_2	H_3	H_4
$e^1{}_2$	0	0.6262	0	0
$e^2{}_2$	0	0	0.4131	0
$e^3{}_2$	0	0	0	0.7313

Table XI Conditional Probabilities for Dornenburg's Ratio Method

	H_1	H_2	H_3	H_4
$e^1{}_3$	0.4541	0	0	0
$e^2{}_3$	0	0.0386	0	0
$e^3{}_3$	0	0	0.3754	0
$e^4{}_3$	0	0	0	0.0657

Table XII Conditional Probabilities for Key Gas Method

Combining these probabilities using the ER algorithm gives the intermediate evaluation shown in Table XIII.

	H_1	H_2	H_3	H_4
f_1	0	0.2673	0.1919	0.1746
f_2	0	0.2746	0.1154	0.4461
f_3	0.3270	0.0158	0.2364	0.0277

Table XIII Intermediate Evaluation Table

The second simpler ER algorithm is now used to combine the evidence in the intermediate table and delivers an overall evaluation of the transformer's condition (Table XIV).

H_1	H_2	H_3	H_4	*No Fault*
0.0608	0.2787	0.2308	0.3567	0.0731

Table XIV Final Overall Evaluation Table

Table XIV indicates only a 7.31% chance of *No Fault* which is relatively small compared with a 35.67% chance of *Arcing*. The official NGT diagnosis is “Failed due to Arcing between insulated No Load Tap Changer shaft pin and coupling of drive”, which coincides with the diagnosis from the final overall evaluation. Based upon the above results, we can declare that our system has not only correctly identified the fault, but also has done so with a large decision margin, which in itself provides further inferred support to the decision making.

By comparison, each of the traditional methods cannot provide this extra level of inferred support and all but one of the methods return an inconclusive decision. The key factor in the representation of the results from the new system is the fact that: the probability of the *No Fault* case is very small, clearly highlighting a danger to the transformer; whilst the presence of a previous cellulose overheating problem and the correct diagnosis of the arcing fault are also presented, helping the engineer to understand more clearly what has occurred within the transformer of interest.

V. Conclusions

Whereas traditional methods try to tackle the problem of DGA as one of classification as do further attempts to solve the DGA problems (Lin *et al*. 1993, Islam *et al*. 2000), ER in effect mimics the processes that the engineer uses to tackle the DGA problems. The above process has been proven to be a much more successful manner. In combination with the softening of the decision boundaries of the traditional DGA methods, a new solution to DGA information handling has been developed in this paper. Furthermore, the new system has also the power to be readily expanded by adding any conceivable diagnosis systems to the second level of the decision tree, the only proviso being that they too can provide results in the required format. For future work the author sees the possibility of optimisation of the decision through the training of the weights used in ER, which can be achieved by reinforcement learning, tailoring the decision made by the system to the one that is required using sets of past data and online diagnosis of the transformer's condition.

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VI. Biographies

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