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A FUZZY INFORMATION APPROACH TO INTEGRATING DIFFERENT TRANSFORMER DIAGNOSTIC METHODS

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Abstract - Methods to identify transformer fault conditions before they deteriorate to a severe state include dissolved gas analysis, liquid chromatography, acoustic analysis, and transfer function techniques. All of these methods require some experience in order to correctly interpret observations. Researchers have applied artificial intelligence concepts in order to encode these diagnostic techniques. These attempts have concentrated on only a single technique and have failed to fully manage the inherent uncertainty in the various methods. In this paper, a theoretic fuzzy information model is introduced. An inference scheme which yields the "most" consistent conclusion is proposed. A framework is established that allows various diagnostic methods to be combined in a systematic way. Numerical examples demonstrate the developed system.

Keywords - Expert Systems, Fuzzy Measures, Fuzzy Sets, Information Theory, Transformer Diagnostics.

1. INTRODUCTION

Proper functioning of power transformers is critical to secure operation of the power system. Methods to identify fault conditions before they deteriorate to a severe state have attracted great research interest. While the most commonly applied method is dissolved gas analysis (DGA) [1], other useful methods include liquid chromatography [2], acoustic analysis [3], and transfer function techniques [4]. The best analysis may arise from aggregating information from more than one of these techniques. All of these methods are imprecise and require experience in order to correctly interpret observations. That is, there are no good strict and general rules which can be applied in all cases. For example, the concentration of dissolved gases that would indicate a possible fault depends on loading history, transformer construction, oil volume, and the manufacturer, among other considerations.

Generally speaking, imprecision is characteristic of many complex diagnostic problems. Broad experience with a technique may be necessary to overcome this imprecision and perform effective diagnosis. Representing this information in an expert system requires an adequate model of uncertainty. Fuzzy mathematics have been developed to manage just this type of uncertainty. Recently, fuzzy mathematic applications within power systems have been proposed in several areas, e.g., [5,6].

This inherent uncertainty in transformer diagnosis techniques has led several researchers to apply fuzzy set methods. In [7,8], fuzzy logic is used to implement DGA methods. An acoustic technique also applied fuzzy logic to representation of uncertainties [9]. These approaches considered a single diagnostic method. Furthermore, only a fairly simple form of fuzzy logic was employed. In particular, the more general framework associated with fuzzy measures and bodies of evidence was not pursued. A more general approach is proposed here in order to systematically manage uncertainties that arise from different diagnostic techniques.

In the developed expert system, each diagnostic method is represented by a rule-base. Each rule consists of a fuzzy relation and an expression of the importance of this relation. Within any rule-base, conflicts arising between rules are resolved to find the most "consistent" solution. Analysis is performed separately for each diagnostic method. Lastly, the diagnoses are combined into a single analysis. During this aggregation, more weight is attached to more certain diagnoses. Advantages of the developed approach include robustness in the face of missing or inaccurate data and easy expansion to new diagnostic methods. Furthermore, the fuzzy mathematics provide an analytical basis for assessing performance which is lacking in simple rule-based expert systems.

This paper is organized as follows. A brief introduction to transformer diagnostic methods and fuzzy information theory is presented. A new method for adapting fuzzy information theory to diagnostic problems is proposed. Specific implementation issues are detailed. Results of tests for the developed expert system are discussed.

2. TRANSFORMER DIAGNOSTIC METHODS

Transformer diagnostic techniques are well-known and are only briefly reviewed here. The most widely applied method is DGA. Incipient electrical and thermal faults will release gases into the transformer oil. Thus, high concentrations of dissolved gas indicate possible fault conditions. Gas production is dependent on the type and energy of a fault. The ratios between different gas concentrations, then, can be used to classify faults. In Table 1, the IEC criteria [1] are shown. This standard allows classification of faults when measurements fall into the specified categories. In addition to these criteria, one must perform some sort of trend analysis. An older or heavily loaded transformer with no fault will have a high concentration of gases that have built up over a time.

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Case No.	Classification of Fault Type	$\frac{C_2H_2}{C_2H_4}$	$\frac{CH_4}{H_2}$	$\frac{C_2H_4}{C_2H_6}$
0	No fault	< 0.1	0.1-1.0	< 1.0
1	Low energy partial discharges	< 0.1	< 0.1	< 1.0
2	High energy partial discharges	0.1-3.0	< 0.1	< 1.0
3	Low energy discharges	0.1-3 to > 3	0.1-1.0	< 1.0-3.0 to > 3
4	High energy discharges	0.1-3	0.1-1.0	> 3.0
5	$< 150°$C thermal fault	< 0.1	0.1-1.0	1.0-3.0
6	150-300°C thermal fault	< 0.1	> 1.0	< 1.0
7	300-700°C thermal fault	< 0.1	> 1.0	1.0-3.0
8	$> 700°$C thermal fault	< 0.1	> 1.0	> 3.0

Table 1: IEC Criteria

Such factors can be accounted for by establishing trends with regular gas samples. The above forms a reasonable starting point for DGA, however, other considerations can be important, including: measurements of other gases, so-called "key-gas" methods and overall gas concentrations. Gas buildups are a function of many factors, e.g., loading history, transformer construction, oil volume, and the manufacturer, among other considerations. The influence of these factors cannot be determined accurately. Thus, any DGA approach is inherently imprecise and requires experience in order to obtain reasonable results.

Recently, researchers have reported on levels of liquid furfural as indicative of insulating paper degradation, e.g., [2]. Such paper degradation is indicative of thermal ageing. At Vattenfall, tests have only just started on this technique. Another method consists of using acoustic sensors to detect (and hopefully locate) discharge activity, e.g., [3]. Unfortunately, this technique is sensitive to spurious environmental noises. It may also be difficult to reproduce conditions which lead to discharges. Others have proposed frequency response measurements, e.g., [4]. This technique is still in the early development stages and suffers from two limitations. First, the transformer must be removed from service in order to perform the test. Second, fault detection may be extremely difficult if a fingerprint response of the transformer in normal condition is not available for comparison. (Although, phase-to-phase comparisons may provide a reasonable fingerprint.) If other evidence of a fault is strong, a simple dc-impedance measurement of each transformer phase as well as insulation resistance measurements can be informative.

Clearly, each of these methods has advantages and drawbacks. When any individual method indicates a problem, that evidence may be clarified by other methods. For example, if DGA analysis indicates discharge activity, it may be prudent to perform an acoustic test before attempting any disruptive inspection. Thus in this work, the various methods are integrated to form a single coherent analysis.

3. FUZZY INFORMATION THEORY

In this section, a general theory of fuzzy information is reviewed. Two types of uncertainty are discussed: fuzzy sets and fuzzy measures. A general framework combining these types of uncertainty forms the basis of fuzzy information theory. A more detailed development can be found in [10].

3.1 Fuzzy Sets

Uncertainties associated with the structure of a class or set of objects can be represented by fuzzy sets. An element of a fuzzy set is an ordered pair containing a set element and the degree of membership in the fuzzy set. A membership function is a mapping:

$$\mu : X \rightarrow [0,1]$$

and for fuzzy set A:

$$A = \{(x, \mu_A(x)) | x \in X\} \tag{1}$$

where X is the universe and $\mu_A(x)$ represents the degree of uncertainty, or, the degree to which x fits the characteristic feature of the set A. A higher value of $\mu_A(x)$ indicates a greater degree of membership. The following definitions of fuzzy set operations are commonly used. If $C = A \cap B$,

$$\mu_C(x) = \min(\mu_A(x), \mu_B(x)) \tag{2}$$

if $C = A \cup B$,

$$\mu_C(x) = \max(\mu_A(x), \mu_B(x)) \tag{3}$$

and if $C = \overline{A}$,

$$\mu_C(x) = 1 - \mu_A(x) \tag{4}$$

Actually, minimum and maximum functions do not tend to correspond well with the way people apply logic, so that, researchers have used a variety of operators [11]. The general framework of [12] is used in this work. Specifically:

$$\mu_C(x) = \frac{1}{1 + ((\frac{1}{\mu_A(x)} - 1)^\lambda + (\frac{1}{\mu_B(x)} - 1)^\lambda)^{\frac{1}{\lambda}}} \tag{5}$$

The parameter λ determines the "nature" and "strictness" of the operation. If $\lambda < 0$ ($\lambda > 0$) then $C = A \cup B$ ($C = A \cap B$). The larger the magnitude of λ, the greater the "strictness" of λ. Notice as $|\lambda| \rightarrow \infty$, (5) approaches (2) or (3).

It is often very useful, to generate a crisp (non-fuzzy) set from a fuzzy set. Define an α-cut as:

$$A_\alpha = \{x \mid \mu_A(x) \geq \alpha\} \tag{6}$$

A_α is a crisp set containing all elements of the fuzzy set A which at least achieve the level α.

3.2 Fuzzy Measures

Uncertainty may arise from the value or identity of some object as opposed to the structure of a set as in the preceding. This uncertainty can be represented by fuzzy measures. In the following development, all sets are crisp unless otherwise indicated. A fuzzy measure g is defined over the power set (or more generally a Borel field) of the universe X as follows:

$$g : \mathcal{P}(X) \rightarrow [0,1]$$

Satisfying:

- Boundary Conditions: $g(\emptyset) = 0$ and $g(X) = 1$
- Monotonicity: for every $A, B \in \mathcal{P}(X)$, if $A \subseteq B$, then $g(A) \leq g(B)$
- Continuity: For any sequence $A_1 \subseteq A_2 \subseteq \ldots$, then $\lim_{i\rightarrow\infty} g(A_i) = g(\lim_{i\rightarrow\infty} A_i)$

With this general definition of a measure, one can define various special cases. If in addition to the above, the following holds:

$$Bel(\bigcup_{1}^{n} A_i) \geq \sum_{i=1}^{n} Bel(A_i) - \sum_{i<j}^{n} Bel(A_i \cap A_j) + \cdots + (-1)^{n+1} Bel(A_1 \cap A_2 \cap \cdots \cap A_n) \quad (7)$$

then g is a belief measure, represented here as Bel. Similarly a plausibility measure, represented here as Pl, is defined if the following holds instead of (7):

$$Pl(\bigcap_{1}^{n} A_i) \leq \sum_{i=1}^{n} Pl(A_i) - \sum_{i<j}^{n} Pl(A_i \cup A_j) + \cdots + (-1)^{n+1} Pl(A_1 \cup A_2 \cup \cdots \cup A_n) \quad (8)$$

When (7) and (8) are equalities rather than inequalities then g is a probability measure, represented as P. Plausibility and belief can also be calculated from:

$$Pl(A) = 1 - Bel(\overline{A}) \quad (9)$$

$$Bel(A) = 1 - Pl(\overline{A}) \quad (10)$$

Notice, the plausibility of (belief in) an event is always greater (less) than the probability of the event. While probability of some event fixes a value for both truth and falsehood, plausibility and belief measures do not specify a value for the complement. This added flexibility can greatly aid representing uncertainties in expert systems. As an illustrative example, consider the least knowledgeable measurement assignments. Here, the probability distribution would be uniform; plausibility would be one for all non-empty sets; and belief would be zero for all sets but the universe X. In summary, the following hold for every $A \in \mathcal{P}(X)$:

- $Bel(A) + Bel(\overline{A}) \leq 1$
- $Pl(A) + Pl(\overline{A}) \geq 1$
- $P(A) + P(\overline{A}) = 1$
- $Pl(A) \geq P(A) \geq Bel(A)$

3.3 Body of Evidence

In a complex problem, information may be obtained from various sources. The most appropriate description, i.e., fuzzy set or one of the associated measures, depends on how the information is received. Thus, a method for combining different sources of information and types of uncertainty is useful. Fuzzy measures can also be defined in the following framework:

$$m : \mathcal{P}(X) \rightarrow [0,1]$$

such that:

- $m(\emptyset) = 0$ and $\sum_{A \in \mathcal{P}(X)} m(A) = 1$

Now, $m(A)$ is interpreted as the evidence on A and only A and is normally referred to as a basic assignment. (Much of the literature uses the term basic probability assignment which, unfortunately, is somewhat misleading.) A specific basic assignment over $\mathcal{P}(X)$ is often referred to as a body of evidence. It can be shown [10] that:

$$Bel(A) = \sum_{B \subseteq A} m(B) \quad (11)$$

$$Pl(A) = \sum_{B \cap A \neq \emptyset} m(B) \quad (12)$$

and conversely that:

$$m(A) = \sum_{B \subseteq A} (-1)^{|A-B|} Bel(B) \quad (13)$$

The basic assignment acts as a common representation for all information. Information from different sources can be translated to a basic assignment and then combined using the Dempster-Shafer rule of combination. That is, given two independent bodies of evidence m_1 and m_2:

$$m_{1,2}(A) = \frac{\sum_{B \cap C = A} m_1(B) m_2(C)}{1 - K}, \quad A \neq \emptyset \quad (14)$$

where:

$$K = \sum_{B \cap C = \emptyset} m_1(B) m_2(C)$$

The factor K is a normalizing factor which accounts for evidence which is unreconcilable.

In a given body of evidence, there may be conflicting or imprecise information. Assessments of such qualities can be computed similar to entropy within probabilistic information theory. Define:

$$C(m) = -\sum_{m(A) \neq 0} m(A) \log Bel(A) \quad (15)$$

$$V(m) = \sum_{m(A)\neq 0} m(A)\log|A| \tag{16}$$

where $|\cdot|$ is cardinality. $C(m)$ and $V(m)$ are referred to as confusion and vagueness, respectively. These measures provide an assessment of the quality of information in the basic assignment. For example, they can be used to determine the amount of information gain obtained from some observation. Furthermore, they are useful in informing the user of the quality of the conclusion obtained by analysis.

4. MAIN RESULT

In the preceding, a description of diagnostic techniques and a very general framework for information aggregation have been described. In this section, the proposed application of these information techniques to diagnostic problems is detailed. A rule structure is defined. Each relation can be used to determine a fuzzy value based on some observation. Since the various diagnostic rules may provide conflicting information, a basic assignment is sought which best resolves conflicts between the rules. Consistency is based on a fault tree for the diagnostic problem. Finally, an information measure is applied in order to assess performance.

4.1 Representing Knowledge - Rule Format

A fundamental characteristic of knowledge-based systems is the simplicity of adding, removing or modifying existing knowledge in the system. Further, missing or erroneous measurements should not invalidate the analysis. In this sense, each relationship in the knowledge-base should be independent. The basic structure of the rule-base in the proposed system uses a fuzzy set description for each relation and a measure of the importance of this relation. A specific measurement is taken and a fuzzy measure of the truth of a relation is calculated from this measurement. For example, consider the following rule:

> **Rule - Excessive H_2**
> IF the level of H_2 is high
> THEN this is indicative of a fault
> REQUIRED to degree 0.4

This rule can be understood as follows; if the H_2 concentration is high then it will support other evidence which indicates a fault. The REQUIRED clause represents situations where even though the H_2 level is not high there may still be a fault. In such cases, other evidence must strongly indicate a fault in order to still reach such a conclusion. The term "high" is represented by a fuzzy set which is dependent on the history of the transformer. In general, the rule format is as follows:

> **Rule R_i**
> IF fuzzy condition A_j
> THEN conclusion B_k
> REQUIRED r (a belief measure)

Given some measurement, a fuzzy value can be determined for A_j. Based on this value and r, a fuzzy value for the conclusion, B_k, can be calculated. The intersection of all rules which apply to this same conclusion must be computed. Thus, the plausibility of a conclusion B_k is calculated at each inference. The initial value $Pl^0(B_k)$ is one and evidence is gathered in order to disprove the plausibility of some proposition. In this way, missing data can be ignored and will not decrease the plausibility of any conclusion. The above is governed by the logical expression:

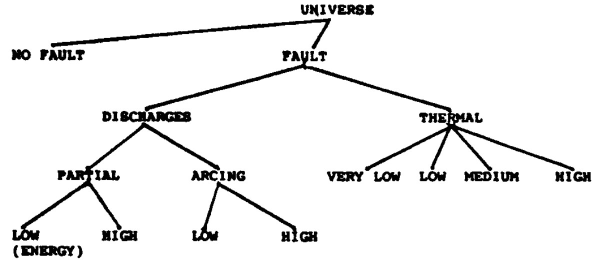

Figure 1: Fault Tree for Transformer Diagnostics

$$Pl^{l+1}(B_k) = Pl^l(B_k) \cap (Pl^{R_i}(B_k) \cup \overline{r(R_i)}) \tag{17}$$

for rule R_i applied after l inferences (each application of a rule to the same conclusion is one inference). The logical operators are those defined for fuzzy sets in (4) and (5).

In section 3, logical operators were defined for fuzzy set membership values only. However with care, logical operators can be applied to combine these values with fuzzy measures. The degree of membership μ should be on the same scale of confidence as some plausibility measure. For example, consider $\mu_A(x_o) = \alpha$, an α-cut A_α, and its complement $\overline{A_\alpha}$. Then, one plausibility measure (which is normally called a possibility measure) over $\overline{A_\alpha}$ is:

$$Pl(\overline{A_\alpha}) = \max_{x_i \in \overline{A_\alpha}} \mu_A(x_i) = \alpha \tag{18}$$

Now, from (10) and (18) we can calculate:

$$Bel(A_\alpha) = 1 - \alpha \tag{19}$$

In this way, fuzzy sets and fuzzy measures yield values which are comparable if the same relative scale is used for both. Logical operators will be assumed to apply to fuzzy values regardless of whether they arise from a fuzzy set or a fuzzy measure.

4.2 Resolving Conflicts and Overall Inference

Since each rule acts independently, there is no guarantee that each rule will yield the same conclusion. Conflicts will arise in many cases (normally all but the obvious situations). Thus, a scheme for resolving conflicts must be determined. It is proposed to find the most consistent basic assignment with the aid of a fault tree.

Consider the fault tree in Fig. 1. The fault tree contains information about the relationship between different fault types. For example, if there is evidence that there is no thermal fault, then all subsets (the different temperature ranges for a thermal fault) are also not solutions. This can also be related to any given strict logical assumption. For example, if there is convincing evidence that there is an electrical fault then, under the assumption of a single fault type, there is convincing evidence of no thermal fault . Whereas without such an assumption, one can draw no inference about the thermal fault. Conflict resolution in this work consists of applying general logic rules to the fuzzy values calculated from a given rule base and adjusting the plausibility and belief measures, accordingly. While practically conflict resolution cannot eliminate conflicts, one can at least "increase" the consistency in a fuzzy information sense. An algorithm has been developed which applies the above reasoning [13].

For each diagnostic method, rules are applied and conflict resolution performed. The resulting body of evidence from each method is combined using (14). The algorithm is detailed below:

Inference Method

1. Select a diagnostic method.
2. Initialize the plausibility of all conclusions to 1.0 and belief to 0.0.
3. Based on given measurements, apply the individual relations of the selected method to the appropriate node in the fault tree using (17).
4. Perform conflict resolution.
5. Calculate $m(A)$ for all nodes in the fault tree from the plausibility and belief measures.
6. Repeat steps 1-5 for each diagnostic method where measurements are available.
7. Aggregate diagnostic methods using (14). (Note: the fault tree structure simplifies computations.)

4.3 Establishing Fuzzy Values

A basic problem in using fuzzy mathematics is establishing fuzzy values. In probability, one can rely on statistics. In fuzzy domains, statistics are not directly applicable and clearly, the fuzzy values are more subjective. On the other hand, the actual fuzzy value is not so important as the relative values assigned. Thus, the most important consideration is to be consistent about assigning values.

In this work, the structure proposed in [14] is used due to its generality and consistency with the logical operation of (5). Specifically, for $x \in [a, b]$:

$$\mu(x) = \frac{(1-\nu)^{\lambda-1}(x-a)^{\lambda}}{(1-\nu)^{\lambda-1}(x-a)^{\lambda} + \nu^{\lambda-1}(b-x)^{\lambda}} \tag{20}$$

where four parameters characterize each transition from 0 to 1: the lower limit a, the upper limit b, the transition rate λ, and the inflection point ν. Decreasing functions and other more complex functions can be constructed from this basic form. Fig. 2 illustrates some typical function shapes. Increasing λ quickens the transition and increasing ν shifts the inflection point to the right.

In the developed system for the DGA method, some parameter values are determined from a statistical analysis of gas data. The upper and lower limits are determined by the range of gas measurements. The inflection point is selected so that the 90 percent level represents the normal. Similarly for ratio rules, the inflection point was set to give about 50 percent leeway on the ration range. Based on several trials, an initial transition rate of $\lambda = 2$ was used for both the membership functions and the logical operators. In cases where a rule incorrectly classifies some relevant case, the inflection point and transition rate were modified to cover this situation. In a few rules, the upper and lower limits were also adjusted.

The above trial-and-error approach is not entirely satisfactory. Where experimental data is available, curve fitting algorithms can be applied to calculate the four parameters in the fuzzy model (e.g., linear regression on a logarithmic transformation

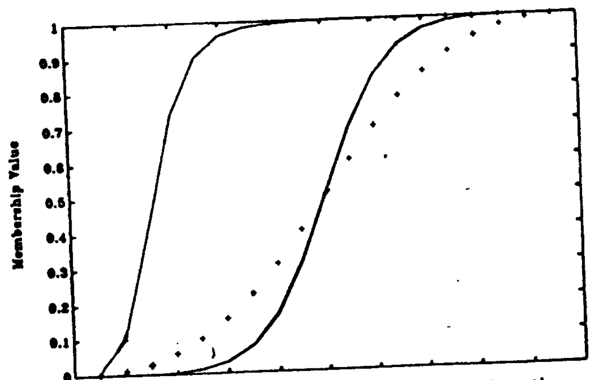

Figure 2: Effect of λ and ν in Membership Functions

[14]). Experience to date suggests that such an approach is of little practical value for two reasons. First, insufficient fault data exists to perform meaningful curve fitting. Second, the diagnostic system is insensitive to minor changes in fuzzy values. Of course, insensitivity is a desired result. It would be inappropriate to develop a system sensitive to values which can only be approximated. The utility of fuzzy mathematics lies in providing sensical answers despite uncertainties not in fixing values for these uncertainties. Still, more sophisticated approaches to assigning fuzzy values are under consideration.

4.4 Interpreting the Analysis

It would be specious to suggest that fuzzy mathematics in its raw form can be easily interpreted by the user. The various computations must be interpreted in some meaningful way. The plausibility and belief measures provide a range of likeliness for the various fault types. This range of values is important information. Some actions can proceed based on a plausibility (e.g., a non-disruptive test) while some actions require firm beliefs (e.g., a disruptive test). Beyond the belief and plausibility measures, there exist the information measures. It is quite possible to have strong supporting evidence on conflicting conclusions. This could imply bad measurements or that some initial assumption (e.g., single fault type) is wrong. An interesting observation is that the information measures are useful guides for both the developer and the end-user.

In the developed system, fuzzy values are given a linguistic value when they fall within some range. (In the current implementation, the terms "little", "some", "significant", "strong" are used). The belief measure provides a lower limit to the uncertainty and the plausibility an upper limit. Thus, a typical conclusion would be "little - some supporting evidence." Furthermore, the information measures are presented to the user. Based on the confusion and vagueness measures the information is classified as: "confusing", "fault type not clear", "reasonable" or "clear". This scheme is simple but provides the basic information. A more detailed interpretation in the same vein could be easily developed.

4.5 Implementation

A rule base for DGA has been implemented. Rules are written for the gas ratios and also to account for historical data for a given transformer according to the experience at Vattenfall. Relations for non-DGA methods have also been written, however, these methods require much more development.

Two fundamental considerations were deemed important in the encoding of the proposed system. First, the programming style should allow for simple modifications and easy implementation. Second, it should be easy to verify the correctness of code. The basic techniques developed in this paper are not particularly difficult to program in a traditional programming style, however, object oriented programming (OOP) techniques were seen as helpful towards attaining these two goals. A strict implementation of OOP techniques was followed. In particular, all class instance variables are protected (i.e., values can only be manipulated by member functions). This ensures that code can be modified and tested on a strictly local basis. Here, absolutely no "global" variables are allowed. The purpose of this guideline is to ensure that the code correctly implements the developed method without any difficult to find "bugs." Further, the rules and fault tree are stored in a database. This allows for simple modification to the knowledge-base.

5. NUMERICAL RESULTS

Table 2 shows the results of analysis for several cases. These cases represent a overview of the type of decisions reached by the proposed system. For each case, the gas concentrations and years in service of the transformer are given, followed by the analysis from the proposed system. Ranges of fuzzy values for the terms discussed in section 4.4 were fixed. For example, strong supporting evidence indicates a fuzzy value greater than 0.75. The values of the information measures (confusion and vagueness) are shown for completeness. Notice that conclusions provide information at several levels. A classification of the fault is given in terms of certainty. Depending on the data, this classification may be very specific, such as, high energy full discharge, or it may be more general, such as, thermal fault. This conclusion is enhanced further by identifying the quality of the evidence, that is, whether there was significant conflicting information in the measurements.

The first 3 cases consider only DGA. In case A, the gas ratios clearly indicate a discharge fault. The relatively high level of gases further suggest the fault is of high energy, although, this conclusion is less certain. Case B depicts a typical case of an older transformer with gas build-up that is still operating normally. In case C, there is strongly supportive evidence of a thermal fault. However, the gas ratios cannot clearly identify the temperature of such a fault. Information analysis identifies the lack of a specific conclusion from the high value of the vagueness measure.

Case D is a hypothetical analysis assuming a furfural measurement has been taken. The furfural concentration strongly indicates accelerated paper degradation. Using this information the analysis more clearly indicates a fault. Notice, the confusion measure decreases after this additional information. The vagueness measure slightly increases as a specific conclusion, "no fault," has been eliminated with only a slight increase in the confidence of the hot spot conclusion.

The developed system has been applied to gas data available on 400kV transformers covering several years (over 800 gas samples) at Vattenfall. It is difficult to know the transformer condition at the time of each gas sample. However, subsequent performance of the transformer will indicate if a serious fault was missed. This information can be used to verify the analysis. In this way, the system provides correct analysis for all of this gas data except in cases of a bad oil samples (usually this results from mishandling in gathering the sample). It is planned to design a filter to identify these bad samples. In-

Year of Installation: 1983
Gas concentrations (ppm): H_2=1058 CH_4=446
C_2H_2=1000 C_2H_4=460 C_2H_6=56 CO=807 CO_2=167

Analysis of transformer condition:
Full discharge (arcing): Strong supporting evidence
High energy (arcing): Some - strong supporting evidence
Low energy (arcing): Little - some supporting evidence

Analysis of information: Reasonable.
(Confusion = 0.858 Vagueness = 0.366)

(A) Transformer with Discharge Fault

Year of Installation: 1953
Gas concentrations (ppm): H_2=50 CH_4=32 C_2H_2=3.7
C_2H_4=110 C_2H_6=22 CO=1500 CO_2=20000

Analysis of transformer condition:
Hot spot (< 150°C): Some supporting evidence
Normal: Significant supporting evidence

Analysis of information: Reasonable.
(Confusion = 0.835 Vagueness = 0.079)

(B) Old Transformer with High Gas Levels

Year of Installation: 1956
Gas concentrations (ppm): H_2=100 CH_4=230 C_2H_2=5.4
C_2H_4=270 C_2H_6=120 CO=880 CO_2=8400

Analysis of transformer condition:
Thermal (hot spot): Strong supporting evidence
Hot spot (> 700°C): Little - significant supporting evidence
Hot spot (300-700°C): Little - strong supporting evidence
Hot spot (150-300°C): Little - significant supporting evidence
Hot spot (< 150°C): Little - some supporting evidence

Analysis of information: Reliable but fault classification is not clear.
(Confusion = 1.037 Vagueness = 1.245)

(C) Indeterminate Fault Type

Year of Installation: 1972
Gas concentrations (ppm): H_2=200 CH_4=680 C_2H_2=88
C_2H_4=1600 C_2H_6=190 CO=1100 CO_2=15000

Analysis of transformer condition (DGA only):
Hot spot (> 700°C): Significant supporting evidence
Normal: Some supporting evidence

Analysis of information: Reasonable.
(Confusion = 0.873 Vagueness = 0.081)

Analysis of transformer condition (DGA and Furfural test):
Hot spot (> 700°C): Significant supporting evidence

Analysis of information: Reasonable.
(Confusion = 0.845 Vagueness = 0.109)

(D) Thermal Ageing with/without Furfural Test

Table 2: Results of Several Analyses

adequate experience at Vattenfall with non-DGA techniques prevents meaningful assessment of the these methods.

6. CONCLUSIONS

This paper has introduced a framework for performing diagnostics using fuzzy information theory. Fuzzy relations are combined with a fault tree to provide the "best" analysis possible. DGA has been implemented with satisfying results. Simple prototypes for other diagnostic methods have been implemented. Several areas require further development:

- In the current implementation, only diagnostic analysis has been performed. It would also be desirable to suggest further measurements which could help clarify the diagnosis in marginal cases.
- As more experience with non-DGA techniques is gained, the knowledge for each these techniques will be refined. Current implementations of the non-DGA methods are trivial.
- While performance is not highly sensitive to the various parameters in the fuzzy model, performance improvement can possibly be obtained by tuning the fuzzy parameters. Only modest improvement is expected due to the limited amount of fault data.
- Validating the proposed system performance consists of presenting cases to an expert for verification. Performance measures need to be developed so that, the developed system can be applied to available data without the need for a human expert to assess the correctness of each solution.

It is clear from the results to date that the developed information techniques provide a powerful and effective representation of diagnostic knowledge. As such, it is felt that this framework can provide a good foundation for performing diagnostics on a variety of power system equipment.

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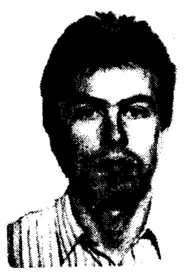

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DISCUSSION

P.K. Kalra and S.C. Srivastava (Indian Institute of Technology, Kanpur) : We congratulate authors for extremely well written paper and advancing the subject of health monitoring of transformers. Authors' response to following queries will be appreciated.

(i) Paper has presented general framework for fuzzy theory for implementing more generalized membership function $\mu(x)$ for fault diagnostics. It could have been interesting to report results of misclassifications for various values of λ and ν. This study could have helped authors to choose optimum value of λ and ν rather than using trial and error method.

(ii) Labeling Figure-2 may improve the understanding of membership function.

(iii) It appears that the authors have established the robustness of fuzzy theory for insufficient and uncertain data. Further, it has been suggested that fuzzy theory has been effective in conflict resolution. It may be worthwhile to compare the approach presented in the paper with induction based decision [A] making approach. Both approaches need learning examples for fast and reliable decisions. Whereas mathematically involved induction based decision making is much less complicated and tree structure for classification is inbuilt. Further the induction based decision making is more robust and can accomodate insufficient and uncertain data for classification.

(iv) Exponential type membership functions may produce results which are comparable to membership functions reported. It is also interesting to observe from Figure-2 that sigmoidal function used for Neural Nets may be one of the good candidates for membership functions.

(v) Case-based reasoning mechanism [B] may prove to be more effective rather than rule based approach implemented in object oriented programming.

(vi) Did authors use any mechanism to minimize the size of the decision tree? How value of 'α' affects the misclassification of faults.

(vii) Function C(m) and V(m) have been defined similar to entropy. Did authors use gain in information from C(m) and V(m) to build decision tree?

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K. TOMSOVIC, M. TAPPER and T. INGVARSSON: The authors wish to thank the discussors for their careful reading of the paper and their interesting comments. The responses are labeled to correspond to the discussors' questions.

(i). A study of misclassifications is more difficult than the discussors suggest. In order to modify membership functions, one must identify which rule or group of rules was the primary cause of the error and modify the rule(s) without creating new misclassifications. In general, attempts at "optimising" membership functions are ill-advised. To suggest that clear well-defined decision regions can be established and thus, classification functions optimised, runs counter to the motivation for employing fuzzy logic. In fact, an indication that a system is well designed and suitable for fuzzy logic is the relative insensitivity of the output to changes in the membership functions. Exactly the opposite of what is desired in an optimisation problem. However, one can use the "entropy" measures to guide modifications. (See comments below.)

(ii). Figure 2 is separated into two figures and reprinted below (the scale is expanded to [0,1000] in x).

(iii) and (v). The two methods suggested by the discussors, inductive learning and case-based reasoning, both tend to work best with a relatively large number of training examples. In the transformer diagnostic problem, there are relatively few fault cases on which to base learning. However, the under-

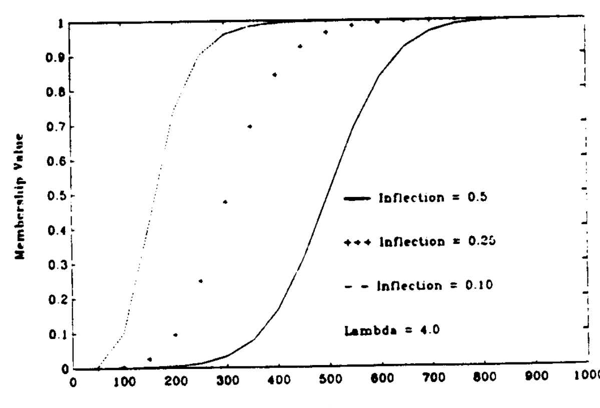

Figure A: Membership functions with varying ν

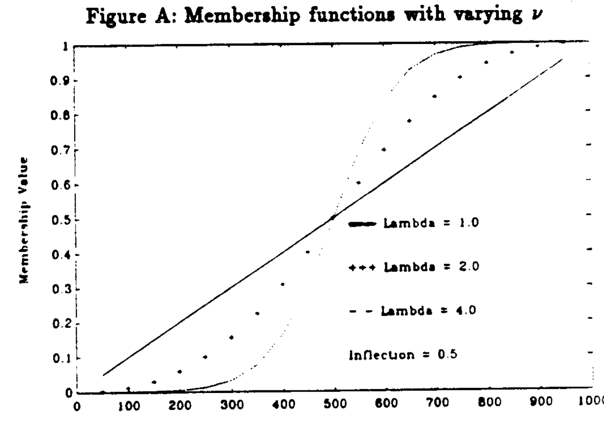

Figure B: Membership functions with varying λ

lying processes leading to failure are understood well enough that some rules can be established. Thus, the rule-based approach appears to be more suitable for this application. On the other hand, it is often difficult to compare approaches in AI until both approaches have been implemented for the problem at hand. With this in mind, the authors would not want to be too discouraging about considering other AI methods.

(iv). The point is well-taken; the relationship to threshold functions in neural nets seems worthy of exploration. In fact, there are many good candidates for membership function types. The form chosen here was selected for consistency with the intersection and union operators. It is believed that using similar forms for operators and membership functions may alleviate some undesired behavior (in particular, high sensitivity near a decision point).

(vi) and (vii). The classification tree as it is used in this work is not as the discussors suggest. The tree is fixed in size and relatively small, so, no trimming or building of the tree is necessary. The "entropy measures" $C(m)$ and $V(m)$ can be used to analyse the quality of the information as well as the gain in information. The emphasis in this paper is on the quality of information. A measure of the gain in information seems to be useful as a guide for deciding when to pursue further measurements. The most effective use of these measures is part of our on-going research.

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