Expert System for Fault Diagnosis of Transformer

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ABSTRACT

This paper presents hybrid expert system for diagnosis of electric power transformer faults. The expert system diagnose and detect faults in oil-filled power transformers based on dissolved gas analysis. As the preprocessing stage, fuzzy information theory is used to manage the uncertainty in transformer fault diagnosis using dissolved gas analysis. The Kohonen neural network takes the interim results by applying fuzzy information theory as inputs, and performs the transformer fault diagnosis. The proposed system tested gas records of power transformers from Korea Electric Power Corporation to verify the diagnosis performance of transformer faults.

Keywords: Expert system, Transformer fault diagnosis, Dissolved gas analysis, Fuzzy information theory, Kohonen neural network.

I. Introduction

Electric power transformer is a major apparatus in power systems, so its correct functioning is vital to system operations. In order to minimize system outages, many devices have evolved to monitor the serviceability of power transformers. Such devices respond only to severe power failures that require immediate removal of the transformer from service, which means electric power outage is inevitable. Therefore, diagnostic techniques for incipient fault detection is important to avoid electrical power outage.

A transformer is subject to two types of stresses, electrical and thermal. The insulating materials within the transformer can be broken down due to the stress yielding gases. Overheating, corona(partial discharge), and arcing(full discharge) are three primary causes of fault related gases. Principally, the fault related gases are hydrogen(H_2), carbon monoxide(CO), carbon dioxide(CO_2), methane(CH_4), acetylene(C_2H_2), ethylene (C_2H_4), and ethane(C_2H_6). The dissolved gas analysis (DGA) has received worldwide recognition as an effective method for the detection of incipient faults. Many diagnostic criteria have been developed for the interpretation of the dissolved gases.[1-3] These methods would find the relationship between the gases and the fault conditions. However, criteria tends to vary depending on the utilities. Each method has limitations and none of them has a firm mathematical description, which means the diagnosis of transformer fault is still in the heuristic stage.

For this reason, intelligent programming is a suit-

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able approach in such diagnostic problems. It can consistently diagnose incipient fault conditions and provides further insight for experts in some cases. Expert systems and neural networks have been used practically in transformer fault diagnosis.[4-7] Expert system derives decision rules from the previous experience while the fuzzy approach represents the decision rules by using vague and ambiguous quantities. Neural network method has also been used for this purpose because the relationships between the fault types and dissolved gases can be recognized by neural network through training process.

In this paper, a hybrid expert system is proposed for transformer fault diagnosis based on the interpretation of DGA. The hybrid expert system incorporates fuzzy algorithm embedded Kohonen neural network (KNN) approach. To demonstrate the performance of the proposed system, thousands of previous of power transformer gas records from the Korea Electric Power Corporation(KEPCO) are tested. More appropriate fault types and fault severity can support the maintenance personnels to increase the performance of transformer fault diagnosis.

Ⅱ. Dissolved Gas Analysis

Fault gases in power transformers are generally produced due to degradation of oil, cellulose, paper, and other insulating materials. Theoretically, if an incipient or active fault is present, the individual dissolved gas concentration, total combustible gas(TCG), and cellulose degradation are all significantly increased. TCG is a mixture of the following gases; H_2, CH_4, C_2H_2, C_2H_4, C_2H_6, CO.

Different patterns of gases are generated due to different intensities of energy dissipated by various faults. Totally or partially dissolved into insulation oil, the gases present in an oil sample make it possible to determine the nature of fault by the gas types and their amount. Therefore, the efforts of many researchers have been made to create simplified diagnosis criteria such as the gas ratio method and the key gas method which in essence are based on this variations in gassing characteristics.

2.1 Gas Ratio Method[1]

Dornenberg, Rogers, and IEC are the most commonly used gas ratio methods. They employ the relationships between gas contents. The key gas ppm values are used in these methods to generate the ratios between them. The ranges of the ratio are assigned to different codes which determine the fault types. Coding is based on experience and is always under modification. However, gas ratio methods are limited in discerning problems when more than one type of fault occurs simultaneously. In addition, for some cases there is no diagnosis for a code as there are more possible combinations of the code than there are for the number of diagnosis. Table 1 displays the gas ratio method as proposed by IEC.

Table 1. Criteria of IEC

Range of gas ratio (volume/volume)		C_2H_2/C_2H_4	CH_4/H_2	C_2H_4/C_2H_6
< 0.1		0	1	0
0.1~1.0		1	0	0
1.0~3.0		1	2	1
> 3.0		2	2	2
Case	Classification of fault type	C_2H_2/C_2H_4	CH_4/H_2	C_2H_4/C_2H_6
0	No fault	0	0	0
1	Low energy corona	0	1	0
2	High energy corona	1	1	0
3	Low energy arcing	1, 2	0	1, 2
4	High energy arcing	1	0	2
5	< 150℃ thermal fault	0	0	1
6	150℃~300℃ thermal fault	0	2	0
7	300℃~700℃ thermal fault	0	2	1
8	> 700℃ thermal fault	0	2	2

2.2 Key Gas Method[2, 3]

Characteristics of "key gases" have been used to identify particular fault types. The suggested relationship between key gases and fault types is summarized as:

H_2: Corona (partial discharge)
O_2 and N_2: Non-fault related gases
CO and CO_2: Cellulose insulation breakdown
CH_4 and C_2H_6: Low temperature oil breakdown
C_2H_2: Arcing (full discharge)
C_2H_4: High temperature oil breakdown

Excluding O_2 and N_2, there are seven fault related gases. The fault condition is indicated by the excessive generation of these gases. Since this method does not give the numerical correlation, the diagnosis depends greatly on experience. Therefore, this technique is simple but it requires much operation time. Table 2 lists the key gas method as applied by KEPCO.[3]

Table 2. Criteria of KEPCO unit: [ppm]

	Normal	Alarm	Fault
H_2	< 400	400~800	> 800
CO	< 300	300~800	> 800
C_2H_2	< 20	20~100	> 100
CH_4	< 250	250~750	> 750
C_2H_6	< 250	250~750	> 750
C_2H_4	< 250	250~750	> 750
CO_2	< 4000	4000~7000	> 7000
TCG	< 700	700~1800	> 1800
Increasing amount	-	≥250/year	≥100/month

Ⅲ. Fuzzy Information Theory

In this paper, fuzzy information theory is used to manage the uncertainty and to incorporate various rules in transformer fault diagnosis using the DGA. Rule base and fuzzy values are selected based on the past experience.

3.1 Rule Structure for Diagnosis

A rule structure is defined in this section. Each relation can be used to determine a fuzzy value based on some observations. In the process of generation of the diagnostic rules, consistency is based on a fault tree for the diagnostic problem, and each relationship in the diagnostics rules is independent. The basic structure of the rule base uses a fuzzy set description for each relation and a fuzzy measure description for the importance of this relation. Fig. 1 shows the structure of the diagnostic rules.

Rule	(rule_name)	R
IF	(fuzzy_condition)	FC
THEN	(fault_conclusion)	C
REQUIRED	(belief_measure)	Bel

Fig. 1 Structure of transformer fault diagnostic rules

In this paper, the diagnostic rules are based on criteria of IEC and KEPCO. Finally, the transformer fault conclusions consist of normal, corona, arcing, and thermal which based on the fault tree for transformer fault diagnosis as Fig. 2.

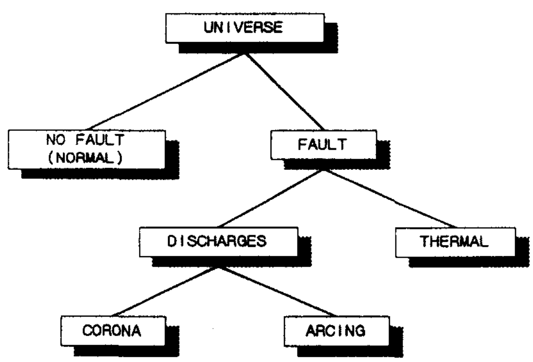

Fig. 2 Structure of fault tree for transformer fault diagnosis

3.2 Fuzzy Sets[8]

A basic problem in using fuzzy mathematics is that how to assign fuzzy values. Generally, one can rely on statistics. In fuzzy domains, statistics are not directly applicable and clear, the fuzzy values are more subjective. Therefore, the most important consideration is to consistent about assigning fuzzy values.

In this paper, the membership function for assigning the fuzzy values used Eq. (1) due to its generality and consistency. Specifically, for $x \in [a, b]$:

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

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. Examples of the membership functions parameters for the gas ratio method and the key gas method are listed in Table 3 and Table 4.

Table 3. Determination of parameter to CH_4/H_2

	ONE	Right side of ZERO	Left side of ZERO	TWO
a	0.35	0.06	1.10	0.75
b	0.06	0.12	0.75	1.16
λ	4.0	2.0	2.0	4.0
ν	0.9	0.5	0.5	0.8

Table 4. Determination of parameter to H_2

	Normal	Right side of alarm	Left side of alarm	fault
a	440	370	850	750
b	350	450	750	850
λ	4.0	2.0	2.0	4.0
ν	0.7	0.5	0.5	0.7

3.3 Fuzzy Measures[8]

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. A fuzzy measure m is defined over the power set(or more generally a Borel field) of the universe X as follows:

$$m: P(X) \rightarrow [0, 1] \tag{2}$$

satisfying boundary condition, monotonicity, and continuity. With this general definition of a measure, one can define various special cases. If in addition to the above, the following holds(specifically, for $A \in P(X)$):

$$Bel(\bigcup_{1}^{n} A_i) \geq \sum_{i=1}^{n} Bel(A_i) - \sum_{i<j}^{n} Bel(A_i \cap A_j) + \cdots$$
$$+(-1)^{n+1} Bel(A_1 \cap A_2 \cap \cdots \cap A_n) \tag{3}$$

then m is a belief measure, represented here as Bel. Similarly a plausibility measure, represented here as Pl, is defined if the following holds instead of Eq. (3). Specifically, for $A \in P(X)$

$$Pl(\bigcup_{1}^{n} A_i) \leq \sum_{i=1}^{n} Pl(A_i) - \sum_{i<j}^{n} Pl(A_i \cup A_j) + \cdots$$
$$+(-1)^{n+1} Pl(A_1 \cup A_2 \cup \cdots \cup A_n) \tag{4}$$

When Eq. (3) and Eq. (4) are equalities rather than inequalities then m is a probability measure. Belief and plausibility measure can also be calculated from Eq. (5) and Eq. (6).

$$Bel(A) = 1 - Pl(\overline{A}) \tag{5}$$
$$Pl(A) = 1 - Bel(\overline{A}) \tag{6}$$

Notice that the plausibility(belief) of an event is always greater(less) than the probability of the event.

3.4 Approximate Reasoning

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

$$Pl^k(C_i) = Pl^{k-1}(C_i) \cap (FC_i \cup \overline{Bel_i}) \tag{7}$$

for rule i applied after k inference(each application of rule to the same conclusion is one inference). Fig. 3 shows the flowchart to inference sequence as the preprocessing stage of the proposed system.

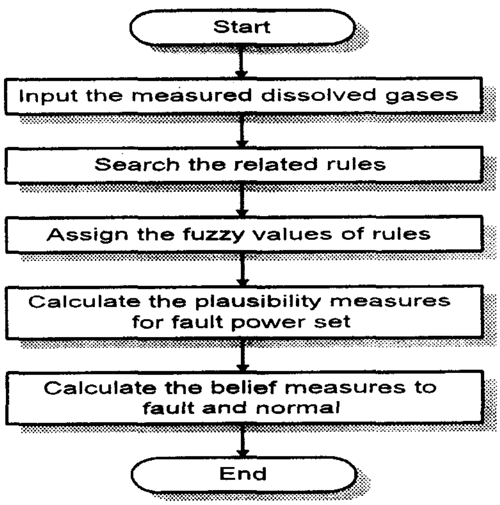

Fig. 3 Flowchart of inference sequence

The following definitions of fuzzy set operations are commonly used as the logical operators.

If $C=\overline{A}$,

$$\mu_C(x)=1-\mu_A(x),\ x\in X \tag{8}$$

If $C=A\cap B$,

$$\mu_C(x)=\min(\mu_A(x),\ \mu_B(x)) \tag{9}$$

If $C=A\cup B$,

$$\mu_C(x)=\max(\mu_A(x),\ \mu_B(x)) \tag{10}$$

Actually, minimum and maximum functions do not tend to correspond well with the way people apply logic, so that, many researchers have used a variety of operators. The general operator is used in this paper, specifically:

$$\mu_C(x)=\frac{1}{1+((\frac{1}{\mu_A(x)}-1)^{\lambda}+(\frac{1}{\mu_B(x)}-1)^{\lambda})^{\frac{1}{\lambda}}} \tag{11}$$

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 $|\lambda|\rightarrow\infty$, Eq. (11) approaches Eq. (9) or Eq. (10). In this paper, based on several trials, a maximum rate of $\lambda=-0.7$ and a minimum rate of $\lambda=0.9$ were used for the logical operators.

Ⅳ. Fuzzy Algorithm Embedded Kohonen Neural Network

The fault diagnosis is a weighted conclusion drawn from a number of data pertinent to the equipment. Its reliability increases with the amount of information available from previous tests and the degree of experience of the laboratory performing the analysis. Therefore, the required rule base could be large and complex.

Highly complex systems can be characterized with very little explicit knowledge using artificial neural networks. The relationship between gas composition and incipient fault condition is learned by the artificial neural network(ANN) from actual experience(through training samples). Obvious and not so obvious(hidden) relationships are detected by the ANN and used to develop its basis for interpretation of dissolved gas-in-oil data. Through training process, ANN can reveal complex mechanism that may be unknown to experts. In contrast, expert system and fuzzy approach can only use explicit knowledge to establish rule base and fuzzy membership function selection. Theoretically, an ANN could represent any observable phenomenon.

An ANN design includes selection of input, output, network topology(structure, or arrangement of nodes) and weighted connections of the nodes. Input feature (information) selection constitutes an essential first step. The feature space needs to be chosen very carefully to ensure that the input features will correctly reflect the characteristics of the problem. The procedure is problem dependent.

4.1 Kohonen Self-organizing Neural Network[9]

In the Kohonen feature map, the competitive learning is the primary identifier. Contrary to updating all connection weights of all the neurons, the competitive learning only changes a few neuron weights based on their activation. For each presented pattern, the competitive learning enables neurons to compete with each other, the neuron with the maximum activation is claimed as the winner neuron. Only the winner neuron and its neighbors are allowed to update. Therefore, the winner neuron and its neighbors are capable of representing the inherent data characteristics.

A KNN consists of an array of n processing elements(neurons) that are arranged on a two dimensional plane. Every element of the input vectors x of m dimensions array is connected to every neuron. The connections from jth component of input vector to the ith neuron are defined as w_{ij}. The network weights represent the property of the input patterns. An example of mapping m dimensional input vectors on the Kohonen layer of 16 neurons is shown in Fig. 4. The number of the neurons on the Kohonen layer is arbitrarily decided. However, the number may influence the classifier performance. A small number of neurons can only complete the coarse discrimination of the training sets, however, a big number may slow the self organization process.

For each presentation of an input vector, a scalar activation function is calculated. This discriminating function is chosen to reflect the dissimilarity between the normalized input vector and the weight vector of the neuron. The favorite measure to the dissimilarity is the Euclidean distance or the product. For a given presentation, the winner neuron is the neuron with the maximum activation.

The neighborhood is a central concept to the Kohonen self organizing feature map. The neighborhoods are the processing units which are close to the winner neuron and those in its neighborhood are updated. Meantime, the neighborhood size decreases to self organize. The strength of weights updates is also adaptively decreases to guarantee the network convergence. Therefore, a neighborhood function is monotonically decreasing in tranining time.

4.2 Implementation

The proposed fuzzy algorithm embedded KNN was also trained and tested on the KEPCO system. The data of this system can be found in [3]. A Kohonen's feature map is shown in Fig. 5. The trained KNN has 2 normal neurons, 8 alarm neurons and 6 fault neurons. Table 5 shows the classification of training patterns. Columns 1 and 5 show the neuron number, and the columns from 2 to 4 and from 6 to 8 show the number of patterns responded to these neurons. Table

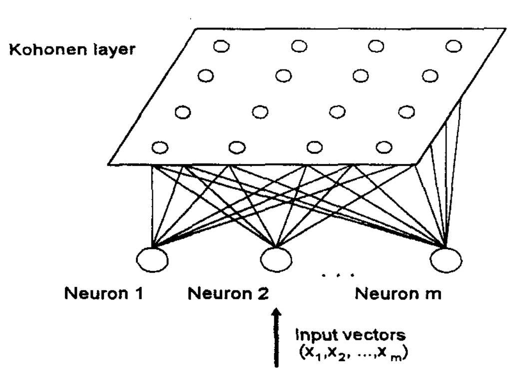

Fig. 4 Structure of Kohonen neural network

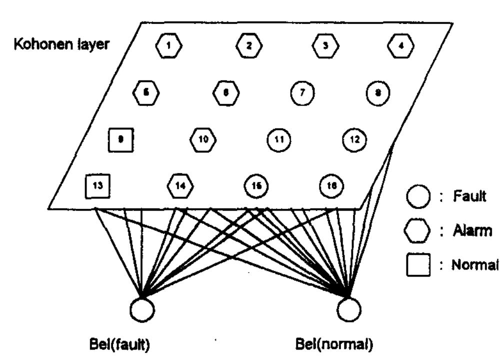

Fig. 5 Result trained by Kohonen neural network

Table 5. Classification of training patterns

Neuron	Normal	Alarm	Fault	Neuron	Normal	Alarm	Fault
#1	1	2	0	#9	26	1	0
#2	0	9	1	#10	0	4	3
#3	0	14	1	#11	0	0	17
#4	2	16	4	#12	0	2	4
#5	1	7	0	#13	70	1	0
#6	0	31	9	#14	0	5	2
#7	0	4	9	#15	0	4	31
#8	0	0	2	#16	0	4	17

Table 6. Test of the Kohonen neural network

Input dimensions	2
Kohonen neurons	16
Initial learning rate	0.5
Initial neighborhood	5
Training patterns	300
Testing patterns	3700
Classification rate	98[%]

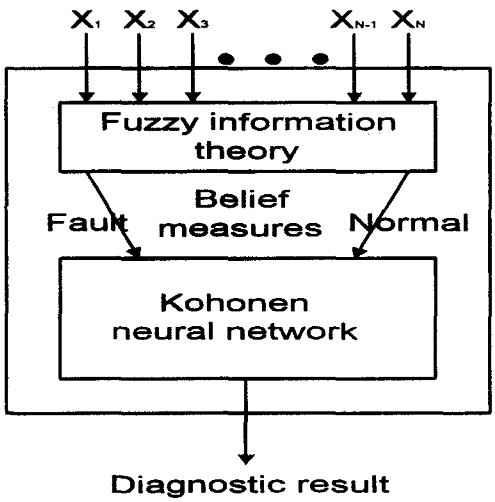

Fig. 6 Structure of the proposed expert system for transformer diagnosis fault (fuzzy algorithm embedded Kohonen neural network)

3 shows the templates of the KNN and tabulates the KNN study cases. Finally, Fig. 6 shows the proposed expert system, fuzzy algorithm embedded KNN, for transformer fault diagnosis using DGA.

Ⅴ. Examples of Diagnostic Results

To demonstrate the validity of the proposed system, we choose 4,000 dissolved gas data of power transformers, that is acquired from KEPCO with 5 years dissolved gas record from 1991 to 1995. We improve the accuracy of diagnostic result about 100 fault data, 700 alarm data, and 3,200 normal data in power transformers. The typical case studies are in Table 7, Table 8, and Table 9, respectively. Table 10 is shown results of case studies applied by KNN. The each shaded region stands for the winner neuron to minimize Euclidean distance in each case study. In this paper, the proposed system offers the diagnostic results which consist of suspected transformer faults and their severity. It is found that more appropriate fault types and fault severity can support the maintenance personnels to increase the performance of transformer fault diagnosis.

Table 7. Case study #1 unit:[ppm]

	CO_2	CO	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6
	940	138	26	558	0	960	365
IEC	Thermal (300[℃]~700[℃])						
Rogers	Unknown						
KEPCO	Fault						
Proposed method	Thermal-Fault						
	Belief measure of fault:0.87			Belief measure of normal:0.09			

Table 8. Case study #2 unit:[ppm]

	CO_2	CO	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6
	838	73	437	76	0	51	25
IEC	Unknown						
Rogers	Unknown						
KEPCO	Alarm						
Proposed method	Corona-Alarm						
	Belief measure of fault:0.32			Belief measure of normal:0.23			

Table 9. Case study #3 unit:[ppm]

	CO_2	CO	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6
	562	113	5	25	0	10	19
IEC	Thermal (150[℃]~300[℃])						
Rogers	Thermal (slight overheating to 150[℃])						
KEPCO	Normal						
Proposed method	Normal						
	Belief measure of fault:0.26			Belief measure of normal:0.67			

Table 10. Result of case studies

Neuron	Type	Case 1	Case 2	Case 3
#1	Alarm	0.72632	0.26226	0.18579
#2	Alarm	0.62174	0.18522	0.27511
#3	Alarm	0.55782	0.10305	0.37101
#4	Alarm	0.48116	0.09930	0.47037
#5	Alarm	0.74112	0.31146	0.13688
#6	Alarm	0.57294	0.19840	0.30095
#7	Fault	0.48922	0.15437	0.40171
#8	Fault	0.38744	0.19002	0.53568
#9	Normal	0.89175	0.47191	0.04151
#10	Alarm	0.67771	0.29218	0.18140
#11	Fault	0.36235	0.25772	0.50125
#12	Fault	0.17923	0.39749	0.70503
#13	Normal	0.87196	0.46727	0.02111
#14	Alarm	0.74276	0.37368	0.10973
#15	Fault	0.21086	0.38837	0.64350
#16	Fault	0.06419	0.51573	0.80935

Ⅵ. Conclusion

This paper studies a hybrid expert system for transformer fault diagnosis. The hybrid expert system presents an intelligent approach to diagnose and detect faults in power transformers using dissolved gas analysis. The proposed system, fuzzy algorithm embedded Kohonen neural network approach, diagnose the suspected transformer fault and their severity. Fuzzy information theory is used to manage the uncertainty in diagnostic problems. And it is also used to perform basic diagnosis using dissolved gas analysis. Kohonen neural network identified the transformer fault as the interim results by applying fuzzy algorithm. Good diagnostic accuracy is obtained with the proposed system.

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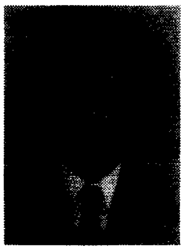

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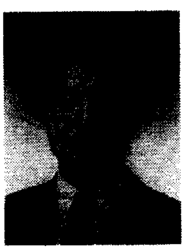

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