1999년도 대한전기학회 하계학술대회 논문집 1999. 7.19-21

유중 가스 분석과 신경 회로망을 이용한 전력용 유입 변압기의 고장 진단

윤용한*, 김재철*, 김재성**
* 숭실대학교 전기공학과, ** 한국전력공사 중앙연수원

A Fault Diagnosis of Oil-Filled Power Transformers using Dissolved Gas Analysis and Neural Network

Yong-Han Yoon*, Jae-Chul Kim*, Jae-Sung Kim**
* Department of Electrical Engineering in Soongsil University, ** Central Training Center of KEPCO

국문 요약 - 본 논문에서는 변압기 유중 가스 분석 자료와 고장에 관련된 특징을 학습시킨 신경 회로망을 이용하여 전력용 유입 변압기의 새로운 고장 진단 방법을 제안하였다. 본 논문에서 제안한 신경 회로망을 이용한 고장 진단 방법(유중 가스 분석 방법)은 입력으로 가스 구성비 분석(IEC 기준) 및 주요 가스 분석(한국 전력 공사 기준) 자료를 채택하였다. 또한, 출력으로 전력용 유입 변압기의 고장 유무 및 고장 종류의 특징을 신경 회로망으로 추출하였다. 따라서 입력된 유중 가스 분석 결과에 따라 전력용 유입 변압기의 진단 결과(고장 유무 인식 및 해석)가 제시되도록 구성하였다. 제안된 신경 회로망을 이용한 변압기 고장 진단 방법은 한국 전력 공사의 변압기 유중 가스 기록으로 효용성을 입증하였다. 따라서 유중 가스 분석만으로 현실성 있는 변압기 진단 및 상태 추정이 가능하게 되었고, 이것의 적용으로 적절한 유지 및 보수 대책 방안을 제시할 수 있게 되었다.

1. INTRODUCTION

The power transformer is a major apparatus in a power system, and 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. These devices respond only to a severe power failure requiring immediate removal of the transformer from service, in which case, outages are inevitable. Thus, preventive techniques for early detection faults to avoid outages would be valuable.

A transformer is subject to two types of stresses, electrical and thermal. The insulating materials within the transformer can break down as a result of stresses to yield gases. Overheating, corona and arcing 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 has received worldwide recognition as an effective method for the detection of incipient faults. Many diagnostic criteria[1-3] have been developed for the interpretation of the dissolved gases. These methods would find the relationship between the gases and the fault conditions. However, criteria tend to vary from utility to utility. Each method has limitations and none of them has a firm mathematical description. Therefore, transformer fault diagnosis is still in the heuristic stage. For this reason, intelligent programming is a suitable approach to implement in a such diagnostic problem. Also, It can consistently diagnose incipient fault conditions for the novice and in some cases may provide further insight to the expert. Expert system and neural network[4-10] have been used practically in transformer fault diagnosis. Specially, artificial neural network[6] method has been used for this purpose since the hidden relationships between the fault types and dissolved gases can be recognized by neural network through training process.

In this paper, based on the interpretation of dissolved gas analysis, a two-step(back propagation) algorithm embedded neural network approach for diagnosis of suspected transformer faults and their severity is proposed. To demonstrate the feasibility of the proposed approach, thousands of power transformer gas records from the Korea Electric Power Corporation(KEPCO) are tested. It is found that more appropriate fault types and fault severity can support the maintenance personnels to increase the performance of transformer fault diagnosis.

2. DISSOLVED GAS ANALYSIS

Fault gases in transformers are generally produced by oil degradation and other insulating materials, e.q., cellulose and paper. Theoretically, if an incipient or active fault is present, the individual dissolved gas concentration, total combustible gas and cellulose degradation are all significantly increased. Different patterns of gases are generated due to different intensities of energy dissipated by various faults. Totally or partially dissolved into the 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[1] and the key gas method[2,3].

2.1 GAS RATIO METHOD

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. For example, Table 1 is the representative criteria suggested by the IEC guide from the Rogers in gas ratio method for interpretation of the gases. 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. IEC codes for the interpretation of dissolved gas analysis

Range of gas ratio [ppm/ppm]	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

Code	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 partial discharge	0	1	0
2	High energy partial discharge	1	1	0
3	Low energy arc discharge	1, 2	0	1, 2
4	High energy arc discharge	1	0	2
5	Thermal fault (< 150℃)	0	0	1
6	Thermal fault (150℃~300℃)	0	2	0
7	Thermal fault (300℃~700℃)	0	2	1
8	Thermal fault (> 700℃)	0	2	2

2.2 KEY GAS METHOD

Characteristics "Key Gases" have been used to identify particular fault types. The suggested relationship between key gases and fault types is summarized in Table 2. There are seven fault related gases. The fault condition is indicated by the excessive generation of these gases. For example, KEPCO suggests criterion for dissolved gas analysis as shown in Table 3, and uses to determine whether a transformer is operating normally or not. Since this method does not give the numerical correlation, the diagnosis depends greatly on experience. Therefore, this technique is simple yet labor intensive.

Table 2. Relationship between key gas and fault type

Key gas	Fault type
O_2 & N_2	No fault related gases
H_2	Corona(partial discharge)
CO & CO_2	Cellulose insulation breakdown
CH_4 & C_2H_6	Low temperature oil breakdown
C_2H_2	Arcing(full discharge)
C_2H_4	High temperature oil breakdown

Table 3. Criteria of KEPCO for the interpretation of dissolved gas analysis [Unit : ppm]

Gas	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	-	≥ 250/year	≥ 100/month

* TCG(total combustible gas) $= H_2 + CH_4 + C_2H_2 + C_2H_4 + C_2H_6 + CO$

The fuzzy-set approach and expert system[4,5,7-10] have been used to incorporate various rules. A knowledge base or a fuzzy membership function is selected based on the past experience. 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 knowledge base could be large and complex.

3. TWO-STEP NEURAL NETWORK

Very complex systems can be characterized with very little explicit knowledge using neural networks. The relationship between gas composition and incipient fault condition is learned by the neural network from actual experience(through training samples). Obvious and not so obvious(hidden) relationships are detected by the neural network and used to develop its basis for interpretation of dissolved gas data. Through training process, neural network can reveal complex mechanism that may be unknown to experts. Theoretically, a neural network could represent any observable phenomenon.

In this paper, back propagation learning algorithm[11] consists of repeatedly passing the training set through the neural network until its weights minimize the output errors over the entire set. One is a neural network for major fault type diagnosis, the other is a neural network for fault severity diagnosis.

3.1 NEURAL NETWORK FOR MAJOR FAULT TYPE DIAGNOSIS

Figure 1 presents the structure of neural network for major fault type diagnosis. In this paper, five input gases C_2H_2/C_2H_4, CH_4/H_2, C_2H_4/C_2H_6, CO, CO_2 are chosen as input features. Several network topologies are compared. The training and testing results of these topologies are listed in Table 4. The ten-fold cross-validation of this optimal is neural network is computed to verify the accuracy.

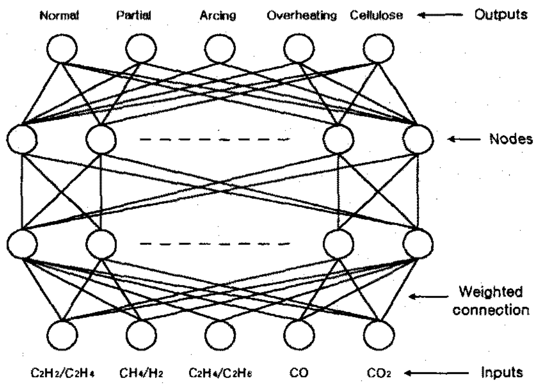

Figure 1. Structure of neural network for major fault type diagnosis

3.2 NEURAL NETWORK FOR FAULT SEVERITY DIAGNOSIS

Figure 2 presents the structure of neural network for fault severity diagnosis. In this paper, the fault severity level consists of normal, alarm, and fault.

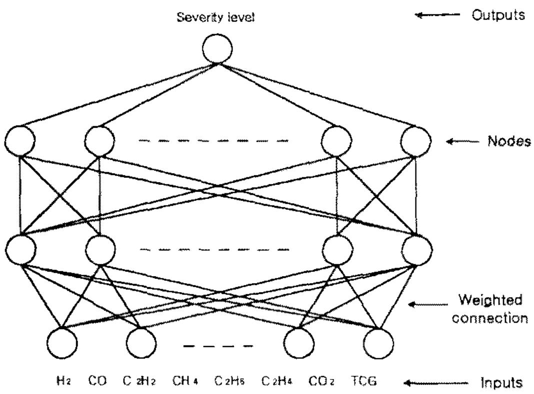

Figure 2. Structure of neural network for fault severity diagnosis

Table 4. Training and testing results of neural network

Neural network Topology(hidden)		Training iteration	Training error	Ten-fold cross-validation
20-10-10	Type	5000	0.018889	95.56[%]
	Severity	4965	0.009998	92.44[%]
30-15	Type	1305	0.009992	97.41[%]
	Severity	2744	0.009999	91.46[%]
50	Type	4158	0.009997	93.70[%]
	Severity	3892	0.009995	97.77[%]

4. EXAMPLES OF DIAGNOSIS RESULTS

Two neural networks were constructed according to the above evaluation. The results between the actual inspection of the transformer and neural network diagnosis match very well. Specially, in the case #4, it is also quite possible to have a condition which involves simultaneous overheating and paper and other cellulose materials

Table 5. Data for case studies

	Case #1	Case #2	Case #3	Case #4
H_2	1398	26	135	165
CH_4	53	558	33	93
C_2H_2	14	ND	76	0
C_2H_4	11	960	45	47
C_2H_6	12	365	49	34
CO	87	138	30	548
CO_2	709	940	942	8263
Severity	Fault	Fault	Alarm	Alarm

* ND : Not detected

Table 6. Results of case studies

	Case #1	Case #2	Case #3	Case #4
Phenomenon	partial	overheating	arcing	overheating[p]
Normal	0.0000	0.0015	0.0007	0.0002
Partial	0.9999	0.0007	0.0078	0.0005
Arcing	0.0064	0.0071	0.9949	0.0028
Overheating	0.0005	0.9992	0.0040	0.9978
Cellulose	0.0033	0.0062	0.0003	0.9921
Severity	0.9817	0.9236	0.5230	0.4722

* p : Paper and other cellulose materials involved

5. CONCLUSIONS

This paper presents an intelligent approach to diagnose and detect incipient faults in power transformers using dissolved gas analysis. The proposed approach, a two-step neural network classifier, diagnose the suspected transformer fault and their severity. Several feature types have been evaluated and several neural network topologies have been considered. The two-step approach makes neural network easier to train and more accurate in detecting faults.

Good diagnostic accuracy is obtained with the proposed system. To demonstrate the feasibility of the proposed approach, thousands of power transformer gas records from KEPCO are tested. It is found that more appropriate fault types and fault severity can support the maintenance personnels to increase the performance of transformer fault diagnosis.

[REFERENCES]

[1] R. R. Rogers, "IEEE and IEC Codes to Interpret Incipient Faults in Transformers using Gas in Oil Analysis," *IEEE Transactions on Electrical Insulation*, Vol. 13, No. 5, pp. 349-354, October 1978.

[2] J. J. Kelly, "Transformer Fault Diagnosis by Dissolved Gas Analysis," *IEEE Transactions on Industry Application*, Vol. 16, No. 6, pp. 777-782, November 1980.

[3] C. H. Nam et al., A Study on The Application of Real Time Analysis System of Dissolved Gases in Transformer Oil, The Report of The Korea Electric Power Research Institute, Taejeon, Korea, Chapter 2, pp. 11-44, June 1995.

[4] C. E. Lin, J. M. Ling, and C. L. Huang, "An Expert System for Transformer Fault Diagnosis using Dissolved Gas Analysis," *IEEE Transactions on Power Delivery*, Vol. 8, No. 1, pp. 231-238, January 1993.

[5] K. Tomsovic, M. Tapper, and T. Ingvarsson, "A Fuzzy information Approach to Integrating Different Transformer Diagnostic Methods," *IEEE Transactions on Power Delivery*, Vol. 8, No. 3, pp. 1638-1646, July 1993.

[6] Y. Zhang, X. Ding, Y. Liu, and P. J. Griffin, "An Artificial Neural Network Approach to Transformer Fault Diagnosis," *IEEE Transactions on Power Delivery*, Vol. 11, No. 4, pp. 1836-1841, October 1996.

[7] Y. H. Yoon et. al., "Expert System for Fault Diagnosis of Transformer," *Journal of Fuzzy Logic and Intelligent Systems*, Vol. 7, No. 1, pp. 45-53, March 1997.

[8] Y. H. Yoon et. al., "A Fault Diagnostic Expert System for Power Transformers using Dissolved Gas Analysis," Journal of The Korean Institute of Illuminating and Electrical Installation Engineers, Vol. 11, No. 2, pp. 80-88, April 1997.

[9] Y. H. Yoon et. al., "A Kohonen Neural Network Approach for Transformer Fault Diagnosis using Dissolved Gas Analysis," Proceeding of The International Conference on Intelligent System Application to Power System at Seoul, Korea, pp. 336-340, July 1997.

[10] Y. H. Yoon et. al., "A Kohonen Network for Fault Diagnosis of Power Transformers using Dissolved Gas Analysis," The Transactions of The Korean Institute of Electrical Engineers, Vol. 47, No. 6, pp. 741-745, June 1998.

[11] S. Haykin, Neural Networks : A Comprehensive Foundation, Macmillan College Publishing Company, Inc., Chapter 10, pp. 397-443, 1994.