Power Transformer Diagnosis Using a Modified Self Organizing Map

J. P. Lee† , P. S. Ji*, J. Y. Lim and S. S. Kim*****

Abstract - Substation facilities have become extremely large and complex parts of electric power systems. The development of condition monitoring and diagnosis techniques has been a very significant factor in the improvement of substation transformer security. This paper presents a method to analyze the cause, the degree, and the aging process power transformers by the Self Organizing Map (SOM) method. Dissolved gas data were non-linearly transformed by the sigmoid function in SOM that works much the same way as the human decision making process. The potential for failure and the degree of aging of normal transformers are identified by using the proposed quantitative criterion. Furthermore, transformer aging is monitored by the proposed criterion for a set of transformers. To demonstrate the validity of the proposed method, a case study is performed and its results are presented.

Keywords: Aging, ANN, DGA, Diagnosis, SOM

1. Introduction

In today's modern industry, customers require electric power supply of the highest quality. Reliability of the equipment operation is essential to maintaining this power quality. Rapid industrial growth necessitates huge electric power consumption and power transmission equipments demand further complexity and expansion. Thus safety and reliability of facilities are more significant factors in the industry. Transformers also tend to need higher voltage and larger capacity because they have great influence on the power system; the safety and reliability of transformers plays an important role in power system stability and assessment. The aging phenomenon may also be preceded in transformers operating normally, causing a fault to arise at any given point. Accordingly, early detection of the aging symptom is very important. Dissolved gas analysis (DGA) is the most popular technique among diagnosis methods of power transformers [1-7].

Dissolved gas analysis (DGA) methods, such as the key gas method, IEC method, Rogers Method and Donenberg method, have been well accepted and widely used by several laboratories, utilities and transformer manufacturers. However, the diagnosis criteria of each method are different from each other and these methods use diverse numerical thresholds for the identification of the various intervals, such that the diagnosis results of each method can be quite dissimilar.

Since the 1990's, new approaches that are based on the traditional DGA have been presented to solve these problems, such as the fuzzy and Artificial Neural Network (ANN) systems [8-13]. However, many researches have investigated the decision rule of normal/abnormal for classifying the causes of aging. Aging degree and causes are mainly analyzed in present researches, but analysis on the aging process is essential to improve the protection technique of transformers.

In this paper, a new approach based on SOM (Self Organizing Map) is introduced to analyze the causes, the degree and the process of aging. The input layer of SOM is changed to obtain a decision making rule that is similar to the human's. Input data are non-linearly transformed by a sigmoid function in the input layer. The aging index is also introduced to present the potential possibility of aging for normal operating transformers. Moreover, the aging process is analyzed based on the aging index to a specific transformer. To demonstrate the validity of the proposed method, a case study is performed and the results are illustrated.

2. Traditional Method of Diagnosis Using DGA

When abnormal phenomena take place in a transformer, insulating oil is chemically decomposed, such that it produces several gases, such as H_2, CO, and hydrocarbons (CH_4, C_2H_2, C_2H_4, C_2H_6) etc. Thus, abnormality of a transformer can be detected by dissolved gas analysis. Degradation diagnosis of the power transformer oil by DGA uses the pattern of the composition of gases and the amount of specified gases.

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In Korea, the Korea Electric Power Corporation (KEPCO) collects oil samples periodically from the transformers in service as well as from the suspected transformers. Samples are subjected to DGA and the status of the transformers is identified according to the criteria shown in Table 1[14]. The results of testing for each transformer are recorded. When a transformer is identified to be in an abnormal state according to DGA, the utility investigates the reason for the state and attempts to prevent a fault in the system.

Table 1 Decision criteria of gas in the insulator and diagnosis period

Division	Normal [ppm]		Alarm [ppm]		Fault [ppm]		Danger [ppm]	
	Below 200 kV	Above 345 kV	Below 200 kV	Above 345kV	Below 200kV	Above 345kV	Below 200kV	Above 345kV
H_2	Below 400		Above 400		Above 800		Above 1,200	
CO	Below 400	Below 350	Above 400	Above 350	Above 700	Above 600	Above 1,000	Above 800
C_2H_2	Below 25	Below 20	Above 25	Above 20	Above 80	Above 60	Above 150	Above 120
CH_4	Below 250		Above 250		Above 750		Above 1,000	
C_2H_6	Below 250		Above 250		Above 750		Above 1,000	
C_2H_4	Below 300		Above 300		Above 750		Above 1,000	
CO_2	Below 5,000		Above 5,000		Above 7,000		-	
TCG	Below 1,000		Above 1,000		Above 2,500		Above 4,000	
Increasing rate	200 Below/month		200 Above/month		200 Above/month		300 Above/month	
DGA period	1 per year		1 per 3 months		1 per month		Immediately	

This incipient diagnoses method of faults in transformers takes place according to the amount of gases obtained from the DGA. The cause of the fault is identified with respect to the concentration of specific gases. The incipient diagnosis results are classified as normal, alarm and faulted states of the transformer. The origins of the faults are identified as partial discharge, insulator degradation, arc discharge, low overheat and high overheat according to the concentration of special gases. However, this type of diagnoses based on the criteria provided in the table is very inflexible. As an example, if the concentration of hydrogen in the transformer oil is above 400 ppm, it is interpreted as the alarm state and the cause of the state is identified to be partial discharges. However, if it is 399 ppm, the transformer is assumed to be operating normally. Even though the difference between the two states is only one ppm, the interpretations are completely different. This indicates a very crisp interpretation on the boundaries. However, even under normal transformer operation, some of these gases may be formed and deposited in the oil. Such an accumulation may result in interpretations that are inaccurate. In fact, the amount of these gases indicates the possible approach towards a care or a faulted state. This fault possibility should be checked periodically by means of DGA to maintain reliable operation of the transformers. Therefore, variation of the existence and concentration of the gases over time must be taken into account for an accurate identification both of the evolution of the fault and the reasons for aging.

3. Proposed DGA Using SOM

3.1 Overview

Objects of this research are the analysis of causes for aging, analysis of aging degree for normal transformers, and analysis of the aging process. This research has been carried out in 5 stages as shown in Fig. 1. At first, input data are transformed using a sigmoid function to solve the boundary problem. Second, the analysis process is performed by SOM using transformed data. Third, a proposed aging index is calculated for analysis of the next stage. At last, the potential possibility of aging is diagnosed by a proposed aging index and the aging process is analyzed using that aging index.

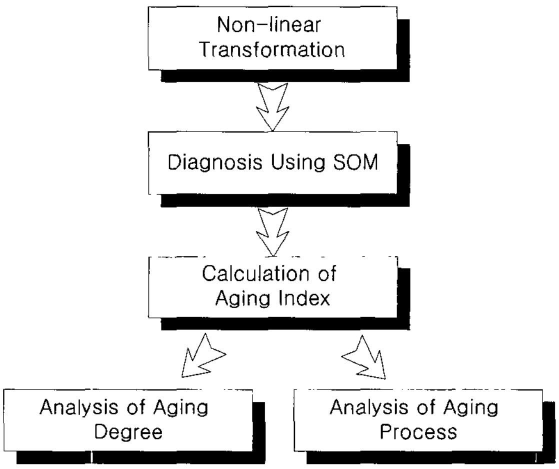


Fig. 1 Proposed approach using SOM

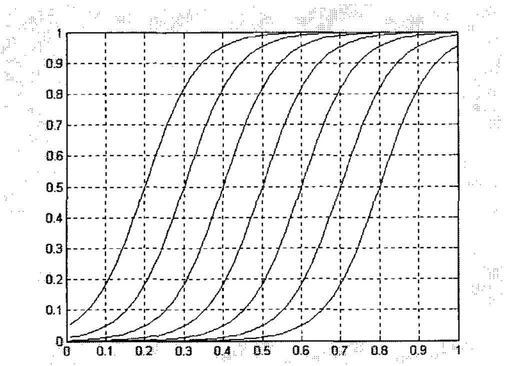
3.2 Nonlinear transform

In this research, input data are non-linearly transformed using a sigmoid function in the input layer. It can be approached much like the decision making process of a human, just as the membership function in the fuzzy theory. The sigmoid function used in this research is as follows.

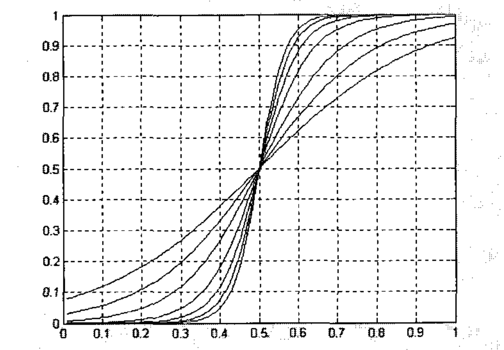
$$f(x) = \frac{1}{1+\exp(-a(x-c))} \tag{1}$$

Where, a : slope of the function
c : center of the function

Fig. 2 shows change of outputs when the slope or center is altered. Output level varies by center position and slope.



(a) Changing center



(b) Changing slope

Fig. 2 Changing of the sigmoid function

3.3 SOM Neural Network

The self-organizing feature map (SOM) is a typical unsupervised neural network that can map nonlinear input patterns from a high-dimensional space to a two-dimensional space [15-16]. It can be thought of as a nonlinear projection of the input pattern on the neuron array that represents the features of input patterns. The projection makes the topological neighborhood relationship geometrically explicit in low dimensional feature space.

The SOM consists of an input layer of neurons in a line and output layer constructed by neurons in a two-dimensional grid as shown in Fig. 3.

The SOM first determines the winning neuron i^* in a competitive layer. Next, the weight vectors for all neurons within a certain neighborhood of the winning neuron are updated using the Kohonen rule,

$$\begin{aligned} {}_i\mathbf{w}(q) &= {}_i\mathbf{w}(q-1) + \alpha(\mathbf{p}(q) - {}_i\mathbf{w}(q-1)) \\ &= (1-\alpha)\,{}_i\mathbf{w}(q-1) + \alpha\mathbf{p}(q) \quad i \in N_{i^*}(d) \end{aligned} \tag{2}$$

where the neighborhood $N_{i^*}(d)$ contains the indices for all of the neurons that lie within a radius d of the winning neuron i^* :

$$N_{i^*}(d) = \{j, d_{ij} \le d\} \tag{3}$$

when a vector $\mathbf{p}$ is presented, the weights of the winning neuron and its neighbors will move toward $\mathbf{p}$. The result is that, after many presentations, the neighboring neurons will have learned vectors that are similar to each other.

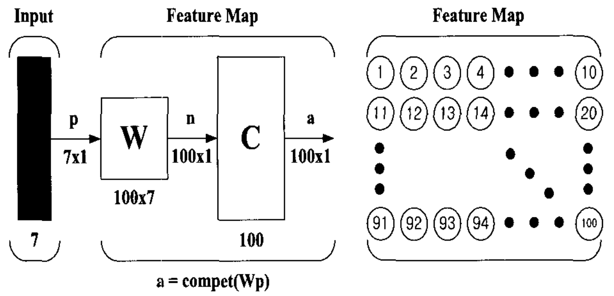


Fig. 3 Self-Organizing Feature Map

SOM is implemented for the topological mapping from a multi-dimensional pattern of dissolved gases onto a two-dimensional plane. When the learning process is finished, mapping on the same neuron signifies that input patterns are identical and mapping on the neighbor neuron signifies that input patterns are similar to each other.

3.4 Aging Index

An aging index is introduced to present potential possibility of the degree of aging for normal operating transformers. The similarity between two vectors can be measured as the difference in length and angle. Thus, it can be defined as (4). In (4), D is equal to 1 when the length and angle of two vectors are equivalent and D is close to 0 when the length and/or angle are different. Therefore, D can be utilized as an aging index to present the potential possibility of aging.

$$D = \frac{|x|}{|y|}\langle x', y' \rangle \tag{4}$$

Where, $x = [x_1, x_2, \cdots, x_n]$,
$y = [y_1, y_2, \cdots, y_n]$,
x', y' : normalized x, y.

4. Case Study

4.1 Historical Data

Data used in this paper is related to the dissolved gas data obtained from KEPCO. It includes the records for 345 [kV] or 154 [kV] transformers operating in two different areas during 1992-1997. There are 963 patterns of DGA data acquired in an area (177 transformers of 64 substations) and 471 patterns acquired in another are (98 transformers of 38 substations). It consists of H_2, O_2, N_2, CO_2, C_2H_4, C_2H_6, C_2H_2, CH_4, CO, and T.C.G. It was acquired by periodic DGA. 963 patterns of DGA data were used for training, and 471 patterns of DGA data were used for verification.

4.2 Diagnosis of Aging by SOM

Power transformers are diagnosed using SOM. The input layer is designed to comprise 7 dissolved gases; namely H_2, CO, CO_2, C_2H_4, C_2H_6, C_2H_2, and CH_4. Input data are non-linearly transformed before entering SOM. Because criteria for "alarm" and "fault" are diverse for each type of gas, parameters of non-linear transformation functions are adjusted to each gas type. Following the non-linear transformation process, SOM is trained. The training data consist of 963 patterns. The output layer as a 2 dimensional-plane made of 10 by 10 neurons. The initial weight vector is determined as the average of each input value for enhanced learning efficiency.

The learning process repeats 866,700 ($100\times9\times963$) times for an accurate mapping. The initial neighborhood, *Nc*, is selected as 9, considering the maximum geometric distance between the neurons on the output layer. It later decreases during the learning process. The learning rate is initially set to 0.01 and decreases exponentially throughout the learning progression.

To verify the training level of SOM, training data are applied to the SOM again. Fig. 4 indicates the output layer of the SOM. Serial numbers indicate the position of a neuron and each area filled in using the same form indicates identical cause of aging.

Table 2 indicates the diagnoses results of SOM for verification data. Diagnosis results of SOM are comparable with that of KEPCO. There are four cases showing different diagnoses results between KEPCO and SOM. In these cases, the amount of specific gases closely approaches the critical value. Because the diagnoses by KEPCO are dichotomous based on Table 1, they could be determined as "normal". But, the proposed method classifies them as "alarm" through non-linear transformation. When dissolved gases approximate to critical values, the aging phenomenon will be advanced due to continuous use of the transformer. Accordingly, these cases must be categorized under "alarm".

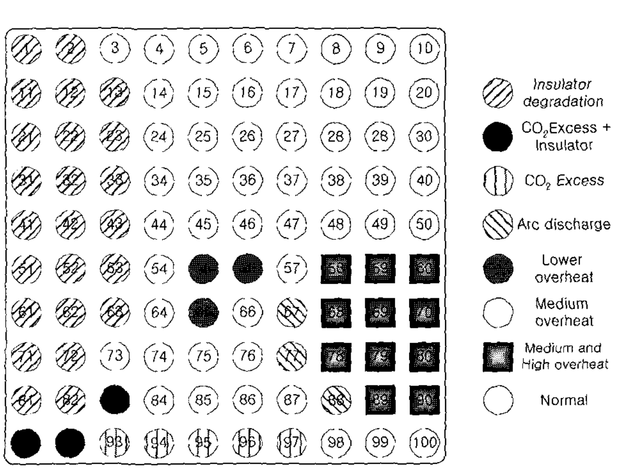


Fig. 4 Training results of SOM

Table 2 Diagnoses results of SOM

Division	Traditional method	Proposed method
Total	471	471
Normal	379	375
Insulator degradation	33	34
CO_2 excess +insulator	1	2
CO_2 excess	9	11
Arc discharge	34	34
Lower overheat	1	1
Medium overheat	3	10
High overheat	7	
Fault	4	4

4.3 Analysis of Aging Degree for Normal Transformer

Since all normal operating conditions exhibit some degree of aging, the proposed aging index is calculated by (4) to identify the degree of aging. The results are illustrated in Table 3. For example, the degree of aging of a normally operating transformer that has been mapped to the 10^{th} neuron is represented by several aging index values associated with several aging reasons. It can be considered "normal" because all index values are very small in this case. Transformers that have been mapped to the 34^{th} neuron have a maximum value 0.6691 to 'Insulator degradation', which signifies that this transformer has the potential for insulator

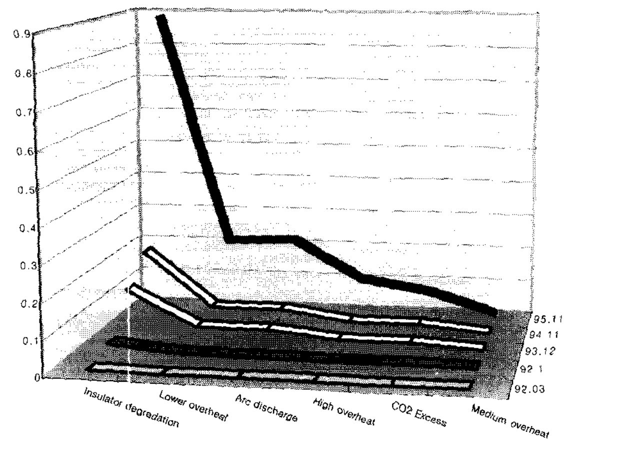


Fig. 5 Aging phenomena due to the operating period of Transformer

Table Analysis result using proposed index

Case	Neuron number	Insulator degradation (41)	Lower overheat (55)	Arc discharge (67)	High overheat (69)	Insulator+ CO_2 excess (92)	CO_2 excess (95)	Medium overheat (99)
1	10	0.0449	0.0207	**0.1101**	0.0320	0.0284	0.0092	0.0067
2	34	**0.6691**	0.1826	0.1644	0.0986	0.4689	0.2384	0.0269
3	54	**0.6896**	0.4334	0.1698	0.0987	0.5151	0.3397	0.1126
4	57	0.0592	**0.6193**	0.2775	0.1551	0.0464	0.0670	0.2611
5	74	**0.6021**	0.1558	0.1366	0.0780	0.5466	0.5293	0.0163
6	85	0.3129	0.1014	0.0635	0.0545	0.4798	**0.7707**	0.0211

degradation. After this manner, transformers that have been mapped to the 57th and 85th neurons have the possibility for 'Lower overheat' and 'CO_2 excess' respectively. However, all of them can be considered 'normal' at this point because they have aging indexes lower than 0.8.

4.4 Aging Process Analysis

Transformers are degraded even under normal conditions. To analyze the evolution of aging with operating time, the aging indexes of some transformers to operating times are calculated for each diagnosis result of SOM. The outcomes are presented in Fig. 5. The transformer in Fig. 5 was first operated in March of 1992 and the diagnosis result at that point was normal. After seven months, it was mapped on the 29th neuron and the maximum aging index was 0.033 indicating 'Insulator degradation'. After a year, the third DGA was performed in December of 1993 once again and it was mapped on the 8th neuron. At the fourth DGA, it was mapped on the 7th neuron. It was still normally operated but the aging index indicating 'Insulator degradation' became greater. Finally, it was mapped on the 1st neuron and its aging index indicating 'Insulator degradation' was 0.8855 on November 1995.

5. Conclusion

Substation facilities in electric power facilities have become increasingly large and complex. The development of condition monitoring and diagnosis techniques has been essential to the improvement of the substation transformer security.

This paper has proposed a method to analyze the cause, the degree, and the process of aging of power transformers by the self organizing map (SOM). Dissolved gas data were non-linearly transformed by a sigmoid function to determine SOM, which is similar to the process of human determination. The potential of failure and the degree of aging of a normal transformer were identified by the proposed quantitative criterion. Furthermore, transformer aging was monitored by the proposed criterion for a set of transformers used in the simulation. To demonstrate the validity of the proposed method, a case study was performed and its results were presented.

Further studies on the architecture of ANN and the parameters of the sigmoid function are needed and the accumulation of reliable data is also required.

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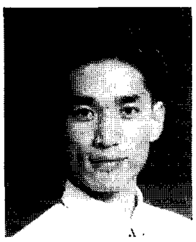

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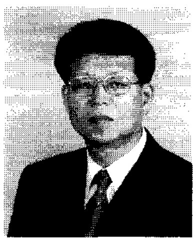

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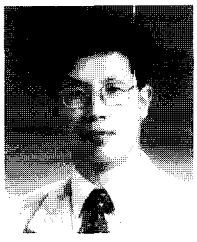

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