Dissolved Gas Analysis of Power Transformer Using Fuzzy Clustering and Radial Basis Function Neural Network

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

Abstract – Diagnosis techniques based on the dissolved gas analysis (DGA) have been developed to detect incipient faults in power transformers. Various methods exist based on DGA such as IEC, Roger, Dornenburg, and etc. However, these methods have been applied to different problems with different standards. Furthermore, it is difficult to achieve an accurate diagnosis by DGA without experienced experts. In order to resolve these drawbacks, this paper proposes a novel diagnosis method using fuzzy clustering and a radial basis neural network (RBFNN). In the neural network, fuzzy clustering is effective for selecting the efficient training data and reducing learning process time. After fuzzy clustering, the RBF neural network is developed to analyze and diagnose the state of the transformer. The proposed method measures the possibility and degree of aging as well as the faults occurred in the transformer. To demonstrate the validity of the proposed method, various experiments are performed and their results are presented.

Keywords: DGA, Diagnosis, Fuzzy Clustering, Power Transformer, RBF

1. Introduction

In extended power systems, substation facilities have become both too complex and too large. Customers require the high quality offered by an electrical power system. However, some facilities have become old and often break down unexpectedly. Such unexpected failure may cause a break in the power system and result in loss of profits. Therefore, it is important to prevent abrupt faults by monitoring the condition of power systems.

Among the various power facilities, power transformers play an important role in transmission and distribution systems. At present, it has been proven that the dissolved gas analysis (DGA) is the most effective and convenient method to diagnose the transformers [1-4]. Under normal conditions, the insulating oil and the organic insulating material in oil-filled equipment generate a small amount of gas caused by the gradual degradation and decomposition [5]. The DGA approach identifies faults by considering the ratios of specific gas concentration. There are various methods based on DGA such as Dornenburg ratios, Roger ratios, IEC ratios, and etc. The DGA is a simple, inexpensive, and non intrusive technique. The advantage of DGA is that the operation and test are performed at the same time, in addition to the fact that it is a simple and inexpensive diagnosis process. However, much uncertainty exists in the data with respect to the dissolved gas. For example, the amount of special gas in normal condition could vary according to the characteristics of the transformer. Furthermore, the DGA method cannot provide accurate diagnosis without the help of experienced experts [6].

Since the 1990's, various artificial intelligence systems, including fuzzy expert systems, adaptive fuzzy logic and artificial neural networks (ANNs) approaches, have been presented to design the diagnosis system more effectively [7-9]. The expert systems based on human experience have showed many successful applications in the industrial fields. However, there are some drawbacks to be fixed, such as that fuzzy membership and diagnosis rule should be constructed on the basis of the expert's experience [10]. To overcome these problems, adaptive fuzzy logic approaches were presented to build the fuzzy rules automatically. However, the number of classification attributes and the fuzzy partition were limited by the simultaneous determination of the membership functions and the inference rules of the fuzzy systems [11].

Fault diagnosis architectures based on neural networks have been proposed to design a simplified structure and obtain higher accuracy compared with the conventional methods. Neural networks have the advantage of learning their optimal parameters and are simple once these parameters are found. Most neural networks have been implemented by multilayer perceptron(MLP) with the back-propagation learning algorithm. However, these

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Received 28 April, 2006 ; Accepted 9 October, 2006

approaches face certain shortcomings. Especially, the training process is slow or shows little convergence when the training data are insufficient and incompatible to ensure proper training [12-14].

In order to resolve these drawbacks, this paper proposes a novel diagnosis method using fuzzy clustering and a RBF neural network. In the neural network, fuzzy clustering is effective for selecting the efficient training data and reducing learning process time. After fuzzy clustering, the RBF neural network is developed to analyze and diagnose the state of the transformer. As compared to the conventional neural networks implemented by MLP with the back-propagation learning algorithm, the RBF neural network has some advantages with respect to learning ability and best approximation property [12-14]. To demonstrate the validity of the proposed method, an experiment is performed and its results are illustrated.

2. Traditional Diagnosis Using DGA

Under the abnormal condition in transformers, the insulation oil and the organic insulation material in oil-filled equipment generate several gases such as hydrogen (H_2), carbon monoxide (CO), acetylene (C_2H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), carbon dioxide (CO_2), and etc. The quantity of the dissolved gas depends fundamentally on the types of faults occurring within power transformers. By considering these characteristics, DGA methods make it possible to detect the abnormality of the transformers.

Table 1 shows decision criteria according to quantity of each dissolved gas in transformers, which means the standard considered in KEPCO (Korea Electric Power Corporation) [14]. More specifically, this method determines incipient faults in transformers according to the amount of gasses acquired from DGA. Here, the incipient faults include normal, alarm, fault, and danger. Also, this method makes it possible to identify the causes of faults represented as partial discharge, insulator degradation, arc discharge, low overheat and high overheat according to the concentration of special gasses.

This diagnosis technique based on these categories has certain limitations. For example, in case of exceeding 400 (ppm) for the concentration of hydrogen, this method determines the fault as an alarm condition and identifies the cause of the fault as partial discharges. However, the transformer is assumed to be operating normally in case of 399 (ppm). Even though the difference between the two data is only 1 (ppm), the interpretations are completely different. This indicates a very crisp interpretation with respect to the boundaries.

On the other hand, a specific gas is generated and accumulated in the oil as time goes on in spite of the normal condition. Therefore, the potential possibility and the degree of aging could be different even to transformers that are in normal condition. In fact, the amount of these gases indicates the potential for seeking a method for finding a faulted condition. This fault detection should be made periodically by means of DGA to maintain reliable operation of the transformers. Therefore, the variation of the existence and the concentration of the gasses with time must be taken into account for an accurate identification of the fault evolution and the aging reasons.

Table 1. Decision categories in KEPCO

Division	Normal[ppm]		Care [ppm]		Fault [ppm]		Danger [ppm]	
	Below 200kV	Above 345kV	Below 200kV	Above 345 kV	Below 200 kV	Above 345 kV	Below 200 kV	Above 345 kV
H_2	Below 400		Above 400		Above 800		Above 1,200	
CO	Below 400	Below 300	Above 400	Above 300	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 4,000		Above 4,000		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	

3. Proposed Diagnosis System using FCM and RBF Neural Network

3.1 Overview

Equations should be placed at the center of the line and provided consecutively with equation numbers in parentheses flushed to the right margin, as in (1). The proposed diagnosis system is illustrated in Fig. 1. It is shown that the system contains four modules, which are normalization, clustering, model formation by RBF, and diagnosis parts.

To make reasonable clustering data, normalization needs to be considered. In this research, input data is normalized by a fuzzy membership function named a sigmoid function. This fuzzy function creates input data with nonlinear scale value ranged form 0 to 1. The normalized value is given by Eq. (1). Here, a and c are the slope and the center of the function, respectively. As seen in Eq. (1), we should set the two parameters (a, c) in advance. This normalization scheme can be expected to perform well if prior knowledge about data distribution among each decision criteria is available. These parameters are determined through the analysis of distribution and extensive experimentation.

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

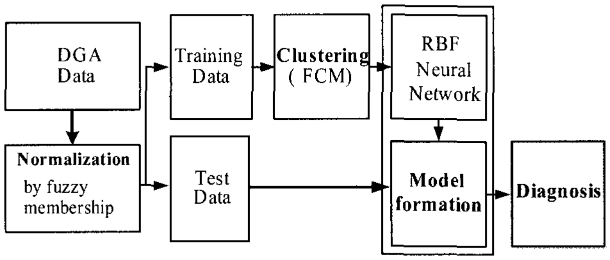


Fig. 1. The diagnosis process for the proposed method

As the next process, fuzzy clustering is implemented to select the efficient training data and to reduce the learning process time. After fuzzy clustering, the RBF neural network is developed to analyze and diagnose the state of the transformer. Finally, the diagnosis is determined by selecting a class with the maximum value among the output layer in the RBF network.

3.2 Data selection by FCM clustering

FCM (Fuzzy c-means) is a data clustering technique whereby each data point belongs to a cluster to some degree that is specified by a membership grade. This technique was originally introduced by Jim Bezdek [15] as an improvement on earlier clustering methods. It provides a method that shows how to group data points that populate some multidimensional space into a specific member of different clusters. FCM partitions a collection of n vectors with q-dimension into c fuzzy groups, and finds a cluster center in each group such that a cost function of dissimilarity measure is minimized. The FCM algorithm can be summarized as follows.

[Step 1] Select the number of clusters $c\ (2 \le c \le n)$ and exponential weight $m (1 < m < \infty)$.

[Step 2] Chose the initial partition matrix $U^{(0)}$ and a termination criterion ε and set the iteration index p to 0.

[Step 3] Calculate the fuzzy cluster centers $c_i^{(p)}$ by using $U^{(p)}$ and data set x_j as follows

$$c_i = \frac{\sum_{j=1}^{n} u_{ij}{}^{m} x_j}{\sum_{j=1}^{n} u_{ij}{}^{m}} \quad (2)$$

[Step 4] Calculate the new partition matrix $U^{(p+1)}$

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}} \quad (3)$$

where d_{kj} means the Euclidean distance between jth center c_j and kth data as follows

$$d_{kj} = d(x_k, c_j) = \left[\sum_{i=1}^{q} (x_{ki} - c_{ji})^2 \right]^{1/2} \quad (4)$$

[Step 5] Compute the cost function as follows

$$J(U, c_1, c_2, \ldots, c_c) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}{}^{m} d_{ij}{}^{2} \quad (5)$$

Stop if either it is below a certain tolerance value or its improvement over previous iteration is below a certain threshold. Otherwise, compute the new cluster centers and fuzzy partition matrix by going back to [Step 3].

3.3 Model construction by RBF neural network

The proposed diagnosis system is implemented by the RBF neural network. The architecture of the RBF neural network is shown in Fig. 2. It is a feed forward multilayer perceptron composed of three layers such as input, hidden and output layer [13, 14].

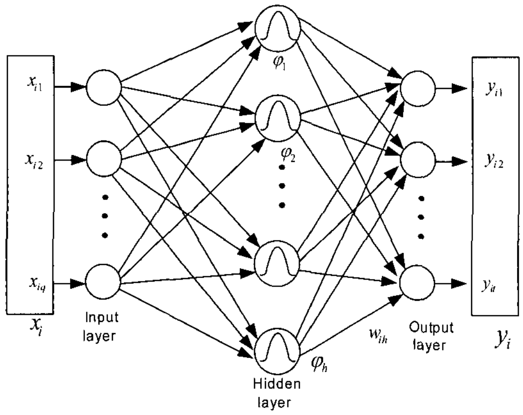


Fig. 2. Architecture of RBF neural network

Let's consider that the input layer has q number of neurons for a q-dimensional input vector. The hidden layer contains several radial basis functions (RBFs) characterized by its center and width. The jth hidden layer unit is usually generated by Gaussian function as follows.

$$\varphi_j(x_i) = \exp\left[-\frac{d(x_i,c_j)^2}{\sqrt{2}\sigma_j^2}\right] \tag{6}$$

$$d(x_i,c_j)^2 = \left(\sum_{k=1}^{q} | x_{ik} - c_{jk} |^2\right)^{1/2} \tag{7}$$

where, x_i is the ith input vector and (c_j, σ_j) are the center and width of the jth hidden layer unit, respectively.

The kth output unit of the RBF neural network for the input vector x_i can be defined as follows.

$$y_{ik} = \sum_{j=1}^{h} \left[\varphi_j(x_i) w_{kj}\right],\ k = 1,2,...t \tag{8}$$

where, w_{kj} is the weight between the jth hidden layer unit and the kth neuron of the output layer, h is total number of hidden units and t is the total number of output units of the PRB network. The sum of square error (SSE) between target value and output value produced by the RBF neural network is defined as follows.

$$E = \sum_{i=1}^{n}\sum_{k=1}^{t}(t_{ik} - y_{ik})^2 \tag{9}$$

The parameters of the RBF neural network such as centers, width and weight are adjusted by gradient-based method to minimize model error. More specifically, these parameters are adapted from initial values to optimal ones [12-14].

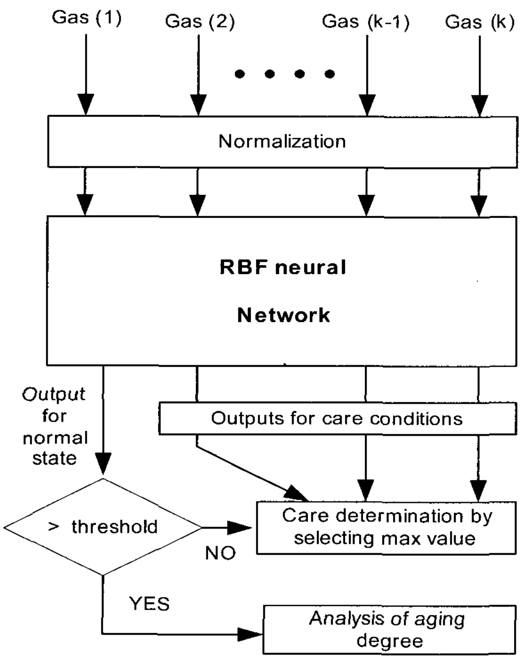


Fig. 3. The diagnosis scheme

3.4 Diagnosis scheme

Fig. 3 shows the diagnosis scheme proposed in this paper. Output nodes include normal state and various alarm conditions.

As the first step in the determination of the state of the transformer, we consider the output value of normal condition. If this value is larger than the predefined threshold, we conclude that the transformer is normal, otherwise it is in care state. In case of normal state, we determine the aging degree according to the output values for normal state calculated by RBF neural network. In case of care state, diagnosis is performed by selecting the care condition with the maximum value among the output values of care conditions.

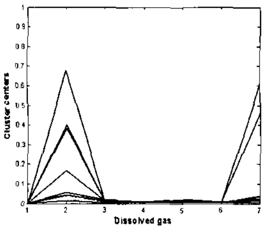
4. Experimental Result and Analysis

4.1 Historical data

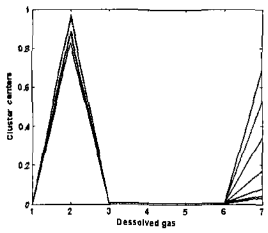
To evaluate the proposed method, we use the dataset acquired by KEPCO. It includes the records for 345kV and 154kV transformers operated in two different areas during 1992-1997. These patterns are acquired from transformers in two regions in Korea. There are 963 DGA patterns acquired from 177 transformers in 64 substations located in the same region and 471 patterns acquired from 98 transformers in 38 substations in another region. Each pattern 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. Among these gases, we chose 963 patterns for the training purpose, while the rest of the data were used for testing.

Fig. 4 shows the cluster centers calculated by FCM. Here, we consider the 7 specific gases such as H_2, CO, C_2H_2, CH_4, C_2H_6, C_2H_4, and CO_2, which are described from number 1 to 7 in this Fig. From this Fig, we see that each condition has the characteristics according to the amount of specific gas. For example, care condition for insulator degradation has more CO gas than the other conditions. Otherwise, the amount of CO gas is less than 0.7 under normal conditions.

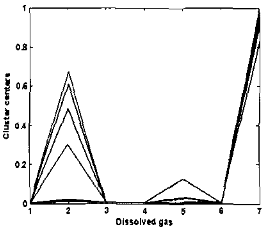
By using the centers calculated by FCM, the RBF neural network is learned or trained by the gradient-based method to minimize the error function. Here the number of inputs equals the kinds of specific gases considered in this architecture. Also, the number of outputs equals the kinds of care conditions plus the normal condition. Care conditions include the six types such as insulator degradation, CO2 excess, arc discharge, low overheat, and high overheat. Therefore the numbers of input and output are 7 and 6, respectively. Also, the number of hidden neurons is 15 and the learning rate equals 0.008. These values are a result of extensive experimentation through which we have concluded that these numeric values produce a good performance of the network. Fig. 5 shows the RMSE (root mean square error) during the 1000 iteration epochs.



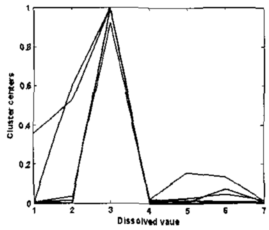
(a) Normal



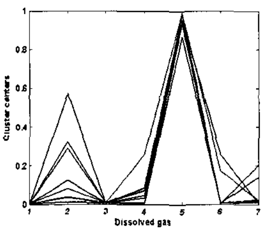
(b) Insulator degradation



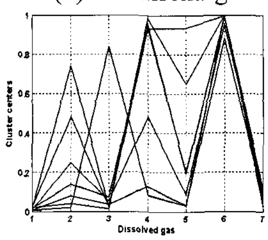
(c) CO2 excess



(d) Arc discharge



(e) Low overheat



(f) High overheat

Fig. 4. Cluster centers calculated by FCM

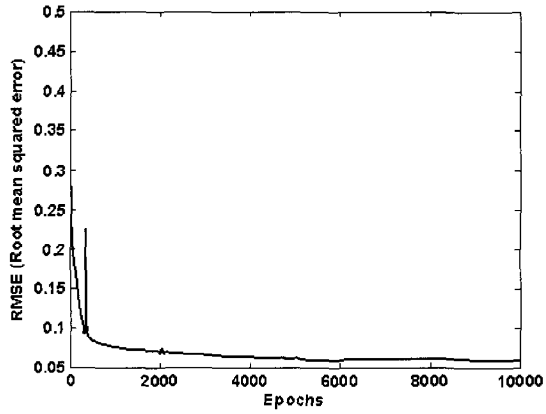


Fig. 5. RMSE during the training process in the RBF neural network

4.2 Diagnosis performance

Fig. 6 presents the output value for the normal condition among the output units in the RBF neural network according to the normal and care dataset determined by experts for normal mode. The values of most of the normal data are higher than 0.4. Otherwise, the output unit corresponded for normal state has the value less than 0.25 for care data. From Fig. 5, we determined the threshold equal to 0.4. If this value is larger than this threshold, we conclude that the transformer is normal, otherwise it is in the care state.

Table 2 shows the diagnosis results with respect to normal and care conditions. From this table, the result by our method is equal to the expert's decision. However, the result for normal data is slightly different from the decisions made by the experts. The reason for this could be well explained by Fig. 6. According to the decision rule performed by KEPCO, if the amount of gas for CO (described as number 2 in the figure) is less than 300, the transformer is determined as normal. Also, if the amount of gas for CO_2 (described as number 7 in the figure) is less than 4000, the transformer is determined as normal. However, two specific gases are close to the boundary of care condition as seen in Fig. 2. More specifically, the values of gases are 287 and 3460 for CO and CO_2, respectively. By considering these relations, our method concludes that this transformer is in care condition. Table 2 indicates the diagnosis performance according to care conditions. As seen in Table 2, the diagnosis performance by our method shows the same decision criteria comparing with the determination by experts except for insulation degradation.

Table 2. Diagnosis performance with respect to normal and care conditions

Expert's decision*		Our method	
Normal	Care	Normal	Care
379	0	364	15
0	92	0	92

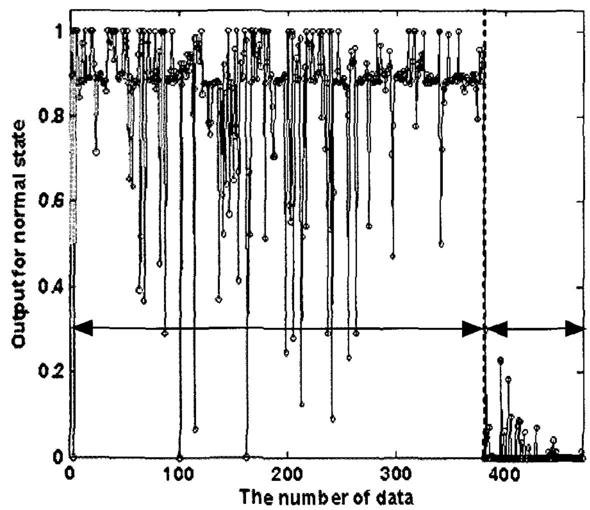


Fig. 6. Output value for normal condition in the RBF neural network

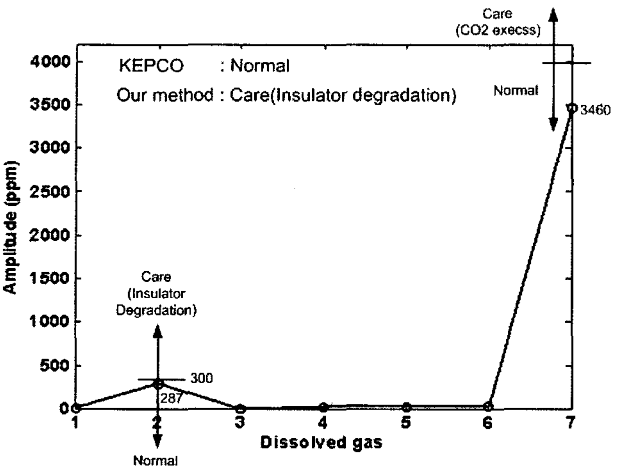


Fig. 7. Dissimilar decision between experts and our method

Table 3. Diagnosis performance according to care conditions

Care conditions	Expert's decision	Our method	Difference
Insulator degradation	35	33	2 Arc (1), CO_2 (1)
CO2 excess	9	9	0
Arc discharge	36	36	0
Low overheat	1	1	0
High overheat	11	11	0

4.3 Analysis of aging degree for normal transformer

Specific gas is generated and accumulated in the oil as time goes on in spite of the normal condition. Therefore, potential possibility and degree of aging could be different even with transformers that are in normal condition. In fact, the amount of these gases indicates a potential of approaching to a care or a faulted condition as well as being in those conditions. For analyzing the aging degree for normal state, we classify the normal condition as three types such as " Good", " Medium", and " Low". This criterion is performed by considering output value of a normal unit in the RBF neural network. More specifically, when the output value is larger than 0.87, our method determines that the transformer is definitely in " Good" condition. Table 4 shows the diagnosis results according to healthy conditions. By applying this technique, we analyze our data according to healthy conditions. As seen in Fig. 9, we see that most transformers are in " Good" condition. Fig. 9 shows the amount of dissolved gas according to healthy conditions for normal transformers. From Fig. 9, the amount of specific gas is increasing according to aging degree such as from " Good" condition to " Low" condition. Fig. 10 indicates the aging degree according to healthy conditions in normal state. This figure displays the aging degree with respect to insulator degradation and CO_2 excess.

From these results, the aging degree increases as the condition changes from "Good" to "Low" condition. Especially, aging degree is close to 40% in case of transformers in "Low" condition. From these experimental results, we are convinced that our method makes it possible to estimate the aging degree for normal transformers as well as the causes of transformers in care conditions.

Table 4. Diagnosis performance according to healthy conditions

Condition	Good (thr> 0.87)	Medium (0.6<thr< <=0.87)	Low (0.4<thr< <=0.6)
Normal (364)	304	45	15

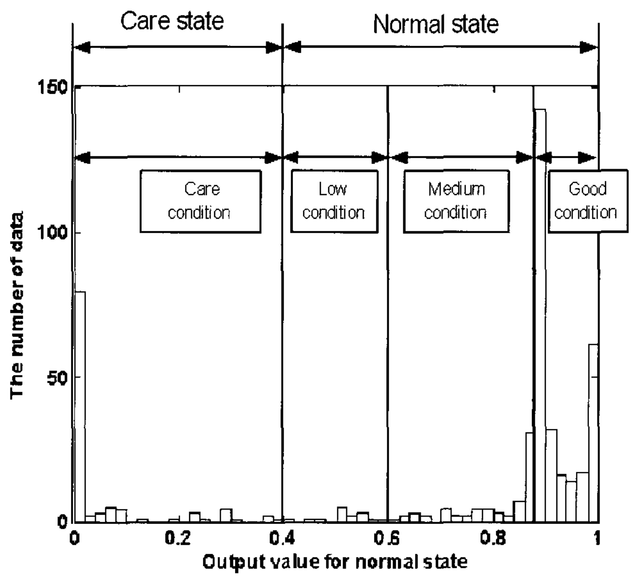
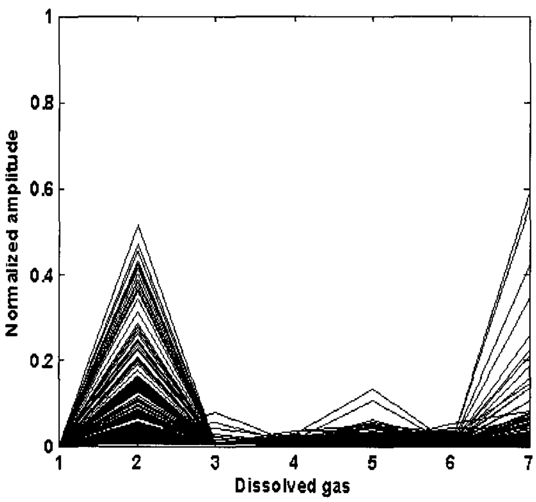
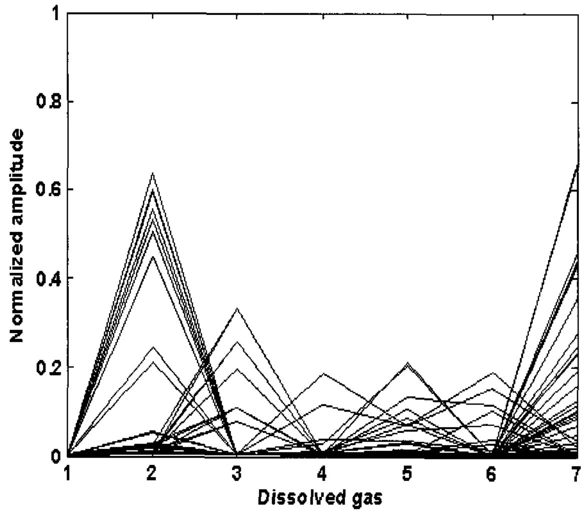


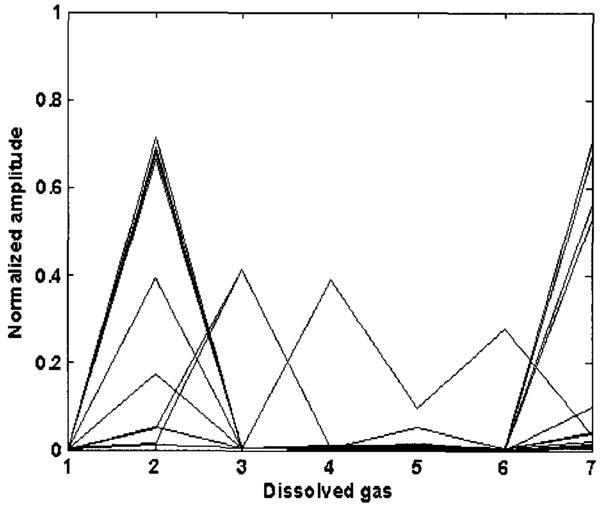
Fig. 8. Data distribution according to healthy conditions



(a) Good condition

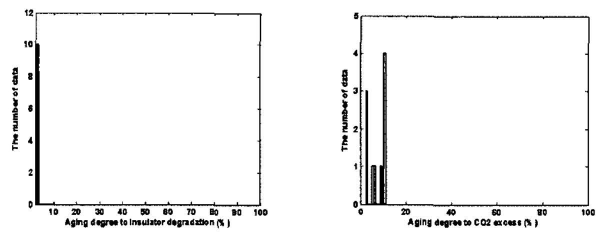


(b) Medium condition

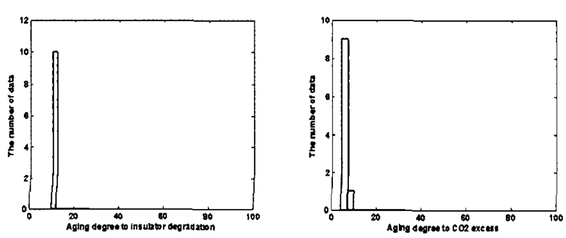


(c) Low condition

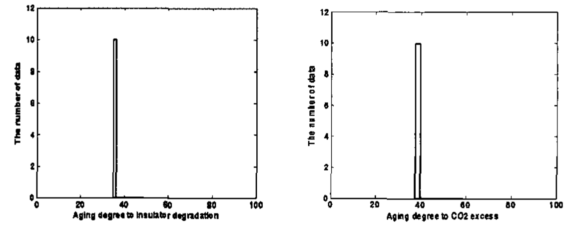
Fig. 9. The amount of dissolved gas according to conditions for normal state



(a) Good condition



(b) Medium condition



(c) Low condition

Fig. 10. Aging degree according to healthy conditions in normal state

5. Conclusion

In this paper, we proposed a method of power transformer diagnosis based on fuzzy clustering and RBF neural network. Prior to applying the neural network, input data is normalized by the fuzzy membership function named sigmoid function. Next, fuzzy clustering is used for selecting the efficient training data and for reducing learning process time. Finally, the degree and the origin of aging were determined by RBF neural networks. From various experimental results, we conclude that the proposed method is efficient in estimating the aging degree for normal transformers as well as the cause of transformers in care conditions.

Acknowledgements

This work has been supported by KESRI(R-2005-7-125), Which is funded by MOCIE(Ministry of commerce, industry and energy).

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