Comparison of Classification Rate for PD Sources using Different Classification Schemes

Seong-Hee Park† , Kee-Joe Lim* and Seong-Hwa Kang**

Abstract - Insulation failure in an electrical utility depends on the continuous stress imposed upon it. Monitoring of the insulation condition is a significant issue for safe operation of the electrical power system. In this paper, comparison of recognition rate variable classification scheme of PD (partial discharge) sources that occur within an electrical utility are studied. To acquire PD data, five defective models are made, that is, air discharge, void discharge and three types of treeinging discharge. Furthermore, these statistical distributions are applied to classify PD sources as the input data for the classification tools. ANFIS shows the highest rate, the value of which is 99% and PCA-LDA and ANFIS are superior to BP in regards to other matters.

Keywords: ANFIS, BP, Clustering, Classification, Partial discharge, PCA-LDA

1. Introduction

Partial discharge (PD) analysis has been established as a reliable diagnostic tool to assess insulation systems for their integrity and design deficiencies. Interpretation of the PD patterns can reveal the source and the reason for their occurrence and therefore has been used as a condition monitoring and quality control tool by the manufacturing industry. For many years, the inter-pretations were performed by human experts. In recent years, advancement of computer hardware and pattern recognition techniques has provided automation and improvement of the PD interpretation process. As a result of computer-aided processing, massive amounts of PD measurements can be interpreted efficiently and reliably [1,7]. PD can provide information on insulation degradation problems in the solid insulator and their application, since PD is a symptom of most insulation failure mechanisms. Therefore, as recognizing accurately a type of PD source, we can obtain a great amount of information related to maintenance and repair of the power system [4-6].

Among the well-known pattern recognition methods applied to PD analysis are expert systems, neural networks, fuzzy classifier, fractal models and statistical methods, among others.

Recently, diverse methods have been introduced to distribute some PD patterns. This paper describes comparison of classification result BP (back propagation), ANFIS (adaptive network based fuzzy inference system) performed preprocessing clustering method and PCA-LDA (principle component analysis-linear discriminant system) method.

This paper made five defected PD occurrence models; air discharge, void discharge, and three types of electrical treeing discharge. Data were acquired from the PD detecting method (IEC 270) and calculated statistical distributions. Then we studied PD distribution characteristics between five defected models. We used these characteristics as input data of the diagnosis algorithm for classification since the purpose of this paper is acquiring the optimum algorithm and scheme for application of an on-line diagnosis system.

2. Comparison Architecture

2.1 Architecture of BP

The BP algorithm is based on MLP (multi layer perceptron). The MLP is a feed-forward network composed of organized topology of interconnected PE (processing elements). The architecture of the BP is shown in Fig. 1. It consists of an input layer, output layer and one or more hidden layers. Learning constitutes the means by which the neural network adapts itself to the desired output [1,5,6]. This adaptation is performed through a change in the weights, which gradually converge to values ensuring that each input vector produces the correct output. There

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are different learning procedures that dictate the neural on how to modify its weight in response to a certain stimulus. The MLP's architecture is composed of forward propagation but the BP learning method is composed of backward propagation. BP is an adaptive network whose nodes (or neurons) perform the same function on incoming signals; this node function is usually a composite of the weighted sum and a differentiable nonlinear activation function, also known as the transfer function. This network is trained in a supervised learning method; it is provided with both input pattern and desired response. It then runs through a series of iterations. It compares its own output with the desired response. And then a match is computed; if there is a match, no change is done to the network; otherwise the weights are modified using the gradient search technique to minimize the mean square error between the desired response and the actual output. Fig. 1 shows the block diagram of the BP learning process and pattern classification process.

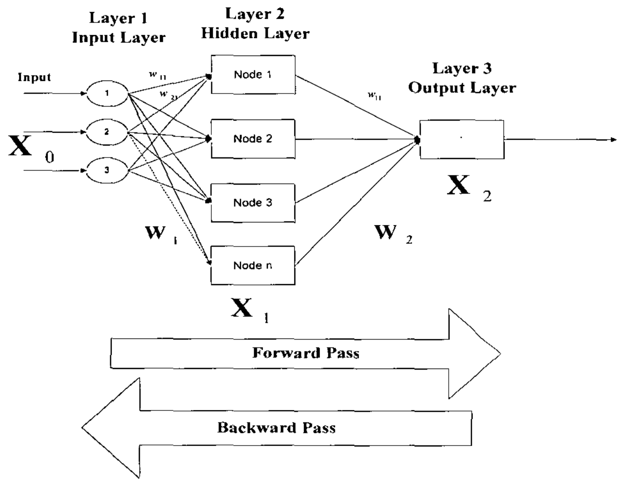


Fig. 1 Architecture of BP

2.2 Architecture of ANFIS preprocessed FCM clustering

The architecture and learning procedure underlying the ANFIS (adaptive-network-based fuzzy inference system) is presented in Fig. 2, which is a fuzzy inference system implemented in the framework of adaptive networks. By using a hybrid learning procedure, the proposed ANFIS can construct an input-output mapping based on both human knowledge and stipulated input-output data pairs. An adaptive network is a multilayer feed-forward network in which each node performs a particular function on incoming signals as well as a set of parameters pertaining to this node. The formulas for the node functions may vary from node to node, and the choice of each node function depends on the overall input-output function that the adaptive network is required to carry out [3,6].

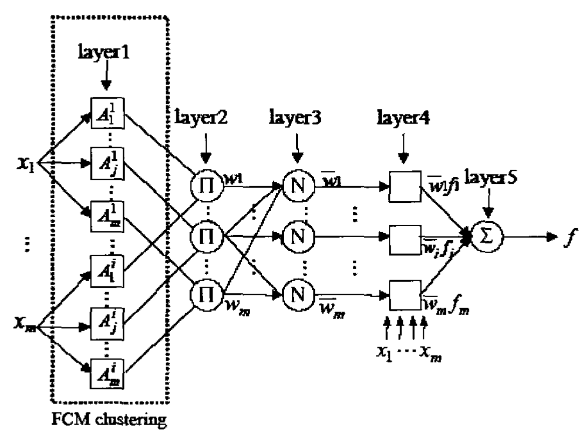


Fig. 2 Architecture of ANFIS with FCM clustering

Fig. 2 shows the architecture of ANFIS used in this paper. It is important that FCM clustering was adapted before ANFIS learning process. Using the rule of clustering can maximize learning process and result.

2.3 Classification method of PCA-LDA

2.3.1 PCA (principle component analysis)

Learning to recognize visual objects, such as human faces, requires the ability to find meaningful patterns in spaces of very high dimensionality [10,11]. Psychophysical findings indicate, however, that "perceptual tasks such as similarity judgment tend to be performed on a low-dimensional representation of the sensory data. Low dimensionality is especially important for learning, as the number of examples required for attaining a given level of performance grows exponentially with the dimensionality of the underlying representation space". PCA is the method behind the Eigenface coding scheme whose primary goal is to project the similarity judgment for face recognition in a low-dimensional space. Note, however, that PCA driven coding schemes are optimal and useful only with respect to data compression and de-correlation of low order statistics. The recognition aspect is not considered and one should thus not expect optimal performance for tasks such as face recognition when using PCA-like coding schemes.

PCA is based directly on leads to dimensionality reduction, and possibly to feature selection.

2.3.2 LDA (linear discriminant analysis)

One of the recurring problems encountered in applying statistical techniques to pattern recognition problems has been called the "curse of dimensionality". Procedures that are analytically or computationally manageable in low-dimensional spaces can become completely impractical in a space of 50 or 100 dimensions. Pure fuzzy methods are particularly ill-suited to such high-dimensional problems since it is implausible that the designer's linguistic intuition extends to such spaces. Thus, various techniques have been developed for reducing the dimensionality of the feature space in the hope of obtaining a more manageable problem [10,11]. We can reduce the dimensionality from d dimensions to one dimension if we merely project the d-dimensional data onto a line. Of course, even if the samples formed well-separated compact clusters in d-space, projection onto an arbitrary line will usually produce a confused mixture of samples from all of the classes, and thus poor recognition performance. However, by moving the line around, we might be able to find an orientation for which the projected samples are well separated. This is exactly the goal of classical discriminant analysis.

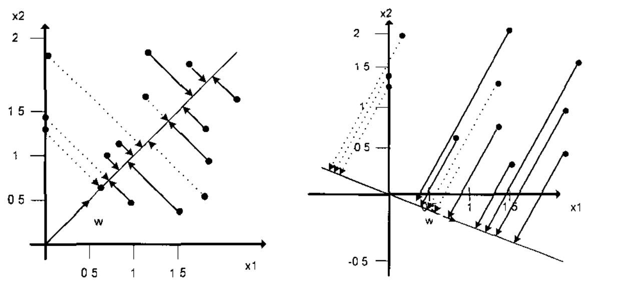


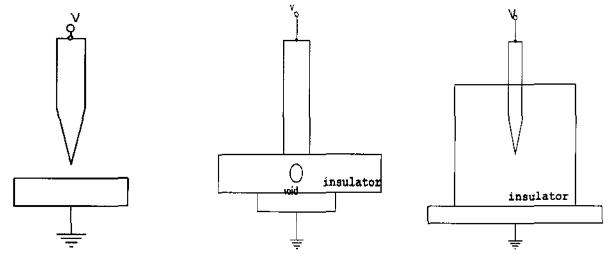
Fig. 3 Projection of the same set of samples onto two different lines in the directions marked w

Fig. 3 shows the projection of the same set of samples onto two different lines in the direction marked point of this paper.

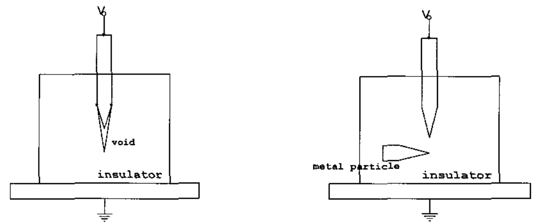
3. Experimental setup

3.1 PD model

Model 1 shows that the needle to electrode and gap distance is 3mm. Model 2 indicates void discharge. An artificially created cylindrical cavity was employed to test the capability of the NN to discriminate between different PD pulse patterns. Test specimen size is 90*90*5 mm, LDPE sheet's cavity diameter is 1 mm, and its depth is 1.3 mm. To avoid surface discharge on the LDPE sheet, the specimen is immersed in insulation oil. Model 3 presents electrical treeing discharge and gap distance of 3㎜ between end of needle and plane electrode. Model 4 illustrates electrical treeing discharge from the void at the electrode edge part. Model 5 indicates the metal particle concluded in the insulator and electrical treeing passing this particle. Models 4 and 5 compose the same material with Model 3.



(a) air discharge (b) void discharge (c) electrical treeing discharge



(d) void electrical treeing (e) metal electrical treeing

Fig. 4 Partial discharge models

(a: air discharge – model 1, b: void discharge – model 2, c: electrical treeing discharge – model 3, d: void electrical treeing discharge – model 4, e: metal electrical treeing discharge – model 5)

3.2 Test procedure and data processing

PD signals were collected with the PD detector system (Biddle instrument, AVTM 662700Ja), which is a computer controlled system for PD data acquisition and analysis. According to IEC 270, the PD pulses are integrated where the maximum value of the integrated signal is proportional to the apparent charge. Fig. 5 shows the block diagram of PD data acquisition.

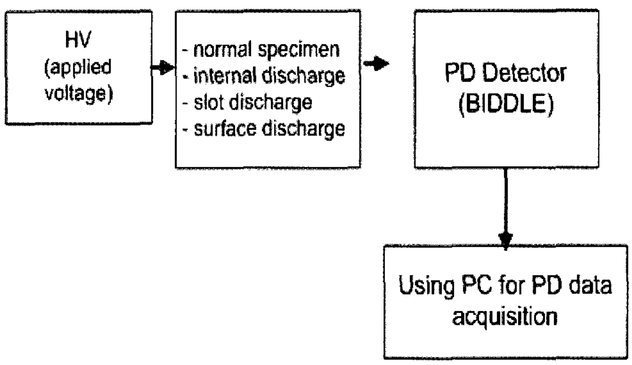


Fig. 5 Block diagram of test procedure for acquisition of PD data

This paper used calculated statistical distribution from the original PD signal as input data of BP and clustering scheme. So, Fig. 6 shows the procedure of PD data for acquiring statistical distribution.

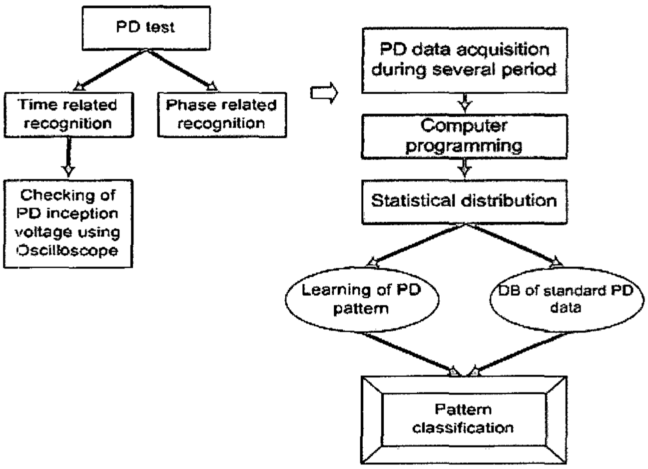


Fig. 6 Block diagram of PD data process

4. PD distribution result

4.1 Distribution of PD signal

The relationship between PD magnitude and intensity as related to PD phase angle can be displayed using a two or three dimensional pattern. In general, for convenience of comparison, two dimensional distributions have been chosen for use. In this paper two dimensional distributions are used to recognize PD. And the BP network is applied to a learning scheme. These distributions were derived from statistical distributions of individual PD events by taking appropriate averages. Three dimensional distribution is φ(phase) - q(discharge magnitude) - n(number of pulse). And two dimensional distributions are q-n, φ-q_a(average discharge magnitude), φ-n, φ-q_{max}(maximum discharge magnitude) distributions. Two dimensional distribution can be presented by four types; Hn(q), Hn(φ), Hqn(φ) and Hq(φ).

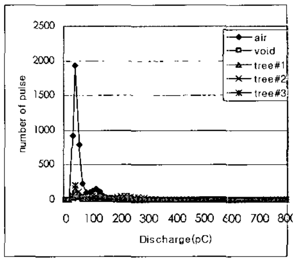
Hn(q) distribution is present pulse count distribution, which represents the number of observed discharges in each discharge magnitude.

Hn(φ) distribution is present pulse count distribution, which represents the number of observed discharges in each phase window as a function of the phase angle.

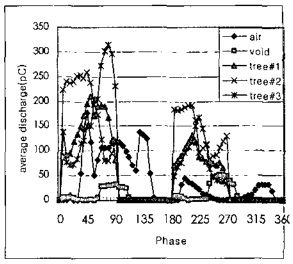
Hqn(φ) distribution is present the mean pulse height distribution, which represents the average amplitude in each phase window as a function of the phase angle

Hq(φ) distribution is present maximum pulse height distribution, which represents the maximum amplitude in each phase window as a function of the phase angle. Fig. 7 is present two dimensional distribution from φ-q-n distribution.

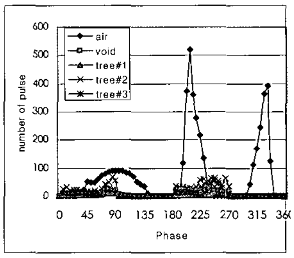
Air discharge stands out among discharge source in number of pulses. This discharge has a different electrode structure, that being needle to plane. If ac voltage is applied to this electrode then inequality of the electric field will be formed. Finally, PD occurred at this electrode above the threshold. On the other side, void discharge formed the same construct in the positive and negative electrodes. So, void discharge's distribution is similar in shape in the case of both positive and negative electrodes but their magnitude is very small compared to the other PD model.



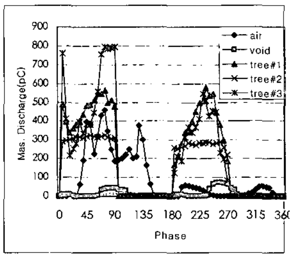
(a) Hn(q) distribution



(b) Hqn(φ) distribution



(c) Hn(φ) distribution



(d) Hq(φ) distribution

Fig. 7 Distribution of PD signal for five models

Three treeing models have different PD distribution in magnitude and number of pulses. Model 5 (contained metal tip in solid insulator) is the biggest PD magnitude followed by Model 4 (with void end of the needle). From the distribution, we know that if it is contained in an abnormal condition (void or metal tip) in the solid insulator, then the treeing process is further accelerated and severed. This is because void and tip have an effect on treeing creation and processing.

5. Result and discussion

5.1 Classification result

This paragraph will describe the classification result for the three models. The three models for classification are air discharge, void discharge, and treeing model #1. Although these distributions are not presented in Chapter 4, their distribution is so different as a result of distribution phase, magnitude and number of pulses.

As a result of Table 1, classification rate of three types of PD models is perfectly 100% in all schemes. This result shows that the PD distribution remarkably differed from among the PD sources. But, if we use all five models, the data indicates that their classification result is not perfect. Between void and treeing model, there exists some error data. So, the total result is not 100%. The outcome of the classification result for five models is indicated in Table 2.

Table 1 Classification result (three PD models)

	Classification scheme		
	BP	ANFIS	PCA-LDA
	Classified result (classified data/input data)		
Model #1	20/20	20/20	20/20
Model #2	20/20	20/20	20/20
Model #3	20/20	20/20	20/20
Classification rate (%)	100%	100%	100%

Table 2 Classification result (five models)

	Classification scheme		
	BP	ANFIS	PCA-LDA
	Classified result (classified data/input data)		
Model #1	20/20	20/20	20/20
Model #2	20/20	20/20	20/20
Model #3	15/20	19/20	16/20
Model #4	17/20	20/20	20/20
Model #5	20/20	20/20	20/20
Total	92/100	99/100	96/100
Classification Rate (%)	92%	99%	96%

5.2 Comparison scheme

This paragraph now shows the comparison scheme. Results are presented in Table 3.

Generally, ANFIS and PCA-LDA methods have more merits than BP and ANFIS because they show the highest

Table 3. Comparison with classification scheme

Items	Classification scheme		
	BP	ANFIS	PCA-LDA
Base system	Neural network	Fuzzy (FCM) + neural network	Feature extraction and Euclidian distance
Recognition rate (%)	92 %	99 %	96 %
Learning cycles (times)	very long (>1,00times)	just several times	not needed
Parameter number	many	few	few
Simplicity	complex	simple	simplest

recognition rate. However, the more increased the ANFIS input dimension, the lower the recognition rate. BP indicates the greatest capability for the learning process among comparison schemes but has several defects for input parameter and learning cycles. Moreover, its recognition rate is the poorest.

Even if PCA-LDA shows lesser recognition than ANFIS, it has the merits of base system, simplicity and input parameter number.

In conclusion, application of scheme for classification of PD sources may be chosen applicably according to size of input data, field and PD sources.

6. Conclusion

This paper describes comparison of BP, ANFIS with FCM clustering and PCA-LDA. As a result we derive the following conclusions.

1. The highest classification result is ANFIS; BP is 92%, ANFIS is 99%, PCA-LDA is 96%.
2. As with other items, ANFIS and PCA-LDA are superior to the BP network.
3. Application of classification for PD sources indicate different dimension of input parameter, data number and PD sources.

However, these results are not absolutely standard as an application of PD source classification. Application on the field is more difficult and needs to consider many things. So, it is important that research on these applications will be performed directly.

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