Development of an Adaptive Neuro-Fuzzy Techniques based PD-Model for the Insulation Condition Monitoring and Diagnosis

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Abstract

This paper presents an artificial neuro-fuzzy technique based partial discharge (PD) pattern classifier to power system application. This may require a complicated analysis method employ -ing an expert system due to very complex progressing discharge form under exter-nal stress. After referring briefly to the developments of artificial neural network based PD measurements, the paper outlines how the introduction of new emerging technology has resulted in the design of a number of PD diagnostic systems for practical application of residual lifetime prediction. The appropriate PD data base structure and selection of learning data size of PD pattern based on fractal dimension and 3-D PD-normalization, extraction of relevant characteristic fea-ture of PD recognition are discussed. Some practical aspects encountered with unknown stress in the neuro-fuzzy techniques based real time PD recognition are also addressed.

Keywords: Pattern Recognition, Adaptive System, Learning System, Neural Network, Fuzzy Logic, Frac-tal Dimension, Chaotic PD Pattern Classification, Dia-gnostic Life Assessment, Incipient Fault Detector, Power Equipment and Power System

1. Introduction

Despite of the growing number of application and development of PD test system, the question how the measured partial discharge quantities relate to the lifetime of a specific test object still remains open.

The fuzziness of measured discharge signal patterns in the real noisy world, such as acoustically, chemically, electrically, thermally or any other methods, can be interpreted as a type of imprecision that stems from grouping elements into classes that do not have sharply defined boundaries. For recognition of our ambiguous, vague measured information of their pattern features from high voltage system, fuzzy set can be a better or effective representation model of measured human data than ideal crisp set information. The characteristic of intuition, prediction, and statistical discharge pattern reconstruction of uncertain information in high voltage system allows a neuro-fuzzy network to deal with situations, or may have some corrupted data, and this can significantly aid the interpretation of the noisy information.

Recently, artificial neural network(ANN) or multi-layered perceptron (MLP) and fuzzy logic(FL), Cha-os-/Fractal engineering methodology has been intro-duced and addressed a variety of applications in many different fields such as system optimization, identi-fication, fault diagnosis, control and stability analysis. ANN and FL has the ability to learn the desired map-ping without knowledge of mathematical relation-ships. Complex relationships between inputs and out-puts (noise corrupted chaotic or stochastic PD-pattern) are distributed on the connection weight of ANN, and the membership function of the FL-system [1-4].

In this respect, this paper presents a new novel adaptive pattern recognizing system concerning analysis of measured PD pattern performed on different high voltage apparatus and models of insulating systems using ANN and fuzzy principles. Some typical results obtained in high voltage system, naturally or artificially aged component models are studied and discussed in respect of practical applicability in the monitoring and diagnosis and maintenance of insulating system.

The advantages provided by this ANN-FUZZY pattern recognizing analyzer system are the possibilities to perform ore reliable identification of aging process and to predict the lifetime of the tested insulating system. Further, in the proposed ANN-FL network inputs can be acoustically or optically chemically measured input information. Outputs of an ANN-FL system provide the information for decision making on the fault condition of a Insulation of high voltage system and insulation life assessment.[5-9]

2. ANN and FL based PD Model for PD Pattern Recognition

The aim of PD pattern recognition or classification is to assign a label to a PD pattern of unknown origin from previously collected patterns with known labels (treeing discharges, corona, etc.). Discharge recognition is also possible by feeding other types of information to the ANN, e.g. the combination of many integrated chemo-physical signal quantities and statistical moments or the parameters which characterize the PD pulse shape measured or by measuring the charge displacement in electromagnetic waves, acoustic waves, light etc. There are many published examples of PD patterns obtained on equipment and samples using computer-aided measurement systems.

A comparative performance between the three different paradigms (Multi-layered Perceptron (MLP)-Back Pro-pagation (BP) ANN network, Kohonen Self-organizing map(SOM), and learning vector quantization(LVQ) network) has been mostly and extensively investigated. This study found in the literature that the back pro-pagation network has the best learning ability when tested using 12 different models of PD sources. How-ever, MLP with BP learning algorithm has shown some problems to find global optimum in parameter space. Genetic algorithm (GA) may help to solve this conflict.

Different types of insulation defects produce different discharge patterns. If these differences can be included in a knowledge base, inference of the defect type from the observed PD pattern may be possible (i.e. an expert system). The presence of small cavities is perhaps the most common cause of discharges in solid dielectric systems. In the literature the discharge patterns associated with a number of typical discharges sources were investigated [6][9].

These defects, artificially created, include single cavity (square, flat, narrow), multiple cavities, electrode-boun-ded cavity, dielectric-bounded cavity, treeing initiated by a cavity and treeing initiated by a conductor.

Different types of solid dielectric were used in making the samples. Phase-Resolved PD Analysis method in-vestigates the discharge patterns in relation to the AC cycle. The voltage phase angle is divided into a number of small windows. Over the integration period, the analysis program calculates the integrated parameters for each phase window and plots these as functions of the phase position φ. The most commonly used distri-butions are (φ-n), (q-n), (φ-q).

Because the brief statistical quantities such as skews, kurtosis, etc. are not effective to characterize the F(φ,q, n) pattern which has a complicated 3 dimensional shape, the neural network applications have been intro-duced as a recognition means of the F(φ,q,n) pattern and have shown excellent performance of the PD pattern recognition. As an example, some of the results in that study is shown in[6]. This gives a comparison for three types of cylindrical cavities in Perspex. For each type, the mean pulse-height phase distribution (q_n,φ) and the pulse count phase distribution (n,φ) are measured and analyzed.

Digital signal processing (DSP) is also a powerful tool which has been used successfully in a number of applications to analyze the PD pulse shape. The digi-tized PD signal is simply a sequence of numbers. DSP is a digital operation performed on such a sequence including feedback operation. The purpose is to extract characteristic parameters associated with the signal or to transform it into another more desirable form. Two of the more important DSP operations are fast Fourier transform (FFT) and digital filtering[6-9].

3. Training PD pattern: F(φ,q,n) pattern

The important parameters to characterize partial discharges are phase angle φ, PD magnitude q and PD frequency n. The F(φ,q,n) distribution consists of the phase angle, the pulse height and the pulse repetition rate as a function of the phase angle and the pulse magnitude. Many other PD characteristics, such as the maximum discharge magnitude, the average pulse ma-gnitude, the pulse repetition rate for given pulse thre-shold can be derived from the F(φ,q,n) distribution. The distribution contains the most of other PD charac-teristics and therefore the distribution was selected as a PD characteristics to recognized the electrode systems. As neural networks require tremendous calculation time to learn patterns, the phase window and magni-tude window number in the F(φ,q,n) distribution pat-tern must be minimized. Recently, fractal features have been also introduced to describe (n-φ-q) patterns. In this case, a (n-φ-q) pattern was reduced to just two di-mensions by calculating fractal dimension and lacuna-rity from the pattern. Fractal dimension describes sur-face roughness, and lacunarity the denseness of the (n-φ-q) pattern, features which are apparently relevant descriptors of the (n-φ-q) patterns [5-6]

Most of typically cases, the neural network is trained by a learning group of input-output pairs which are exam-ples of the mapping that the network is required to compute in supervised learning method. In supervised learning , an error magnitude is defined to the each output neuron according to the external 'teacher'. For the last couple of years, almost research works on 3-d PD using ANN has been concluded by the experienced size of ANN construction.

Our experimental ANN construction represents 120-10-3 of a multilayer feedforward network. The neurons in ANN construction can be divided into three layer: input layer, hidden layer and output layer. The ANN can identify input pattern once the connection weights are adjusted by means of the learning process. Error correction rule called the Back-propagation learning algorithm is most popular method in ANN training. The connection weights of the feedforward network are derived from the input-output patterns in the training group by the generalized delta rule. The algorithm is based on minimization of the error function.

4. Fractal Application for Stress Calculation

The Fractals have been very successful tool to express the naturally occurring phenomena and the shape whi-ch were impossible to descript numeric and quantitative analysis in conventional mathematical methods looks like an Euclidean geometry. In Fractal dimension, we suppose the same pattern as the virtual existence sum of region(Nr) when those size of virtual area is the r (const). The Fractal dimension is following.

$$FD = -\frac{\log(N(r))}{\log(r)} \qquad (1)$$

Our method for FD calculation used to carry out the cover method which was one of the typical negative gradient value in logarithm graph between the virtual existence sum of region(Nr) and the variable size(r) of virtual area. In part of tree research, many researcher has been a tendency to select 2 dimensional observation system more than 3 dimension method, so those non-linear characteristics of 2 dimensional observation me-thod was represented a broad area between bush-type and chestnut-type tree. One of the other serious pro-blem for on-line measurement in the Fractal application is some image noise during the processing. If image data has a some kinds of noise after image processing, Fractal dimension would be calculated to the larger value than original Fractal dimension.

Furthermore, Fractal mathematics has a some boundary for exactly numeric expression of electrical tree in case of 2 dimensional observation. For example, Fractal area from 1.5 to 1.65 shows the saturation characteristics and easily find expression range of the different quan-titative according to a human feeling. We supposed a two kinds of virtual box both N1 and

N2, the those Fractal dimension will be able to following formula (2).

The difference between D1 and D2 above the formula was represented to be proportioned following.

$$D_1 - D_2 \propto \log[\frac{N_2(r)}{N_1(r)}] \qquad (2)$$

Most of typically cases, the Fractal dimension is cal-culated by the virtual existence sum of region(Nr) which are results examples of the size of virtual area(r) in image data. In this paper, we suppose that tree always exists in the some finite region(XYZ) and has a same pattern as the existence sum of region(NT). This new expression was called Semi-Fractal Dimension because SFD results are similar to FD. The supposed formula about SFD is following.

$$OD - SFD = \log(XYZ) - \log(N_T) \qquad (3)$$

Above formula has a special definition in image pattern such a observation dimension(OD), SFD, the sum of existence(NT) in finite region. OD was represented as integer by Euclidean geometry.

5. Application Examples : Some Experimental Study Fractal Dimension

Using the supposed SFD method, we are carry out on the application of same image data used to be calculated in FD processing. Photo 1 is show the results the FD algorithm. The method called FD has a good linear characteristic. But conventional FD method whose purpose is on-line measurement has a long calculation time to numeric expression of electrical stress. The new method called SFD has a good linear charaãteristic and an ability of high speed calculation more than conventional FD. Figure 1 represent the results from SFD algorithm. We easily confirmed linear characteristics of SFD compared with FD. As a results of SFD, we take a quantitative value as electrical stress, resulting from supposed method define the accelerating level.

Although the application of ANN and FL networks to complex partial discharge patterns obtained at this time would appear to be somewhat premature, there is some evidence that in terms of the changes in the partial discharge pulse height distribution patterns it may be possible to predict the breakdown of insulation systems under intense discharge conditions.

However, the most significant advances made in the area of PD pattern recognition primarily concern the discrimination between single discharge sources of different types. For example, in papers' in the referen-ces[6] it was demonstrated that neural networks using the multi-layer perceptron technique can readily distin-guish between the discharge pulse shapes that are due to changes in void size and void surface layer (elect-rode) characteristics when comparing single discharge sources on a one to one basis[6].

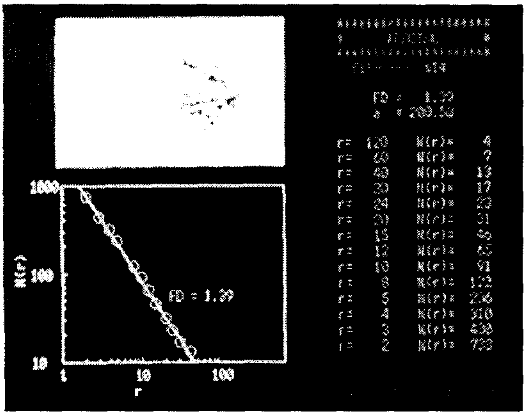

Fig 1. The fractal result after image processing of tree.

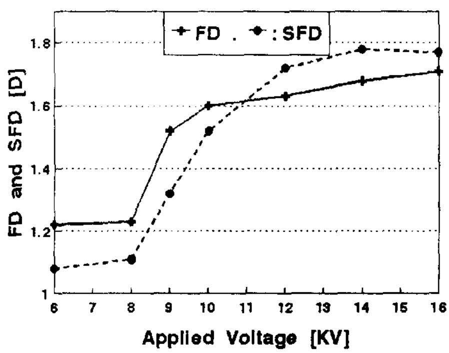

Fig. 2 Semi-fractal and Fractal dimension

The first important step is to select a type of PD pattern that has good discriminating power. Especially (n,φ,q)-PD distribution and its derivatives such as (q_{max},φ); (q_n,φ), etc. distributions have been extensively used for recognition. The shape of individual PD pulses and various frequency spectra provide another way to recognize partial discharges. To reduce the dimension of original PD data, (n,φ,q) distribution, characteristic features or internal knowledge properties of the data should be extracted from the data.

Due to lack of "a priori knowledge or information" of concerned problems, there is no unique way to do this. Statistical parameters (skews, kurtosis) and fractal features (fractal dimension, lacunarity) are just few examples of such features. The trade-off between the number of features, time for the calculation of the features, discriminating power of the features and the final speed of classification should be considered when de-signing the features.

To create a data base for reliable PD recognition, various aspects such as the effects of test voltage level, aging, availability of starting electrons, must be taken into account. A number of mathematical methods are available to organize the data base. Mapping techni-ques and cluster analysis methods can be used for this purpose but it should be realized that there is no 'best' method.

Results presented to date now dealt mostly with re-cognition of single PD sources. Future automated recognition systems should also be able to recognize multiple PD sources and to pinpoint the most dan-gerous one. Possibilities inspired by the chaos- and fractal engineering for monitoring the aging of insu-ation by means of PD recognition should also be further investigated. Currently on-going projects related Research and Development works on this special sub-ject is continuing accompanied with R&D works of ANN- and/or FL-technologies and Fractal- and/or Cha-os Engineering methodologies.

Hence, the works reported in the literature are neces-sarily of a rather preliminary and rudimentary nature, and represents only the beginning in a much more formidable task of applying ANN and FL based Fractal /Chaos pattern recognition techniques on actual power equipment and apparatus with the aim of deriving mea-ningful and reliable information from the PD patterns in the course of routine PD tests.

The present works[6] have demonstrated that even with the most simple of PD patterns and sources the re-cognition capabilities of the ANN and FL evaluated are not always perfect and reliable. Nevertheless, this po-sitive result obtained on very simple artificial models and electrodes should not be misconstrued so as to impel indiscriminate application of ANN-FL in areas where at this stage of their development and in terms of our current knowledge of the discharge process, their PD pattern recognition capabilities are clearly limited.

Complex discharge patterns that are produced by a large number of different source are far more difficult to classify correctly than relatively simple patterns due, for example, to single cavity and electrical tree sources. Much more detailed work on pattern recognition is required at this stage of ANN and FL, Fractal and Chaos engineering and development of relevant techno-logies before a reliable and economic diagnostic system can be developed and carefully verified concerning the interpretation of complex PD patterns on actual insu-lating systems[6].

a) Case Study 1

The learning process was carried out using 100 data of 3-d pattern from 5 kind of SFD during the treeing test. The ANN construction consists of 120-10-3 of a multilayer feedforward network. Connection weights are trained by means of the learning process called the back-propagation learning algorithm. The calculation was done by Turbo C on a IBM-PC. Figure 4. shows the ANN result of unknown PD signal during treeing test with 1.2-1.4 SFD. After ANN learning from data group with 1.25-1.35 SFD, the ratio of aging recog-nition is about 85 % in case of similar SFD test, the corrected result of ANN output cell was decided on above the 0.8 value of predicted output. The first and the second output cell was supposed to the safety area, the third cell was decided on dangerous area that has a possibility to breakdown. However, some area was shown the dam-ping characteristics, those area sup-posed unknown area. Specially, test in a below SFD was easily calculated to the unknown area. Those characteristics was predicted the unclear pattern bet-ween 0 and 1 for ANN discrimination, those results of bellow SFD test becomes widely more than high SFD learning data because of linear progress of tree.

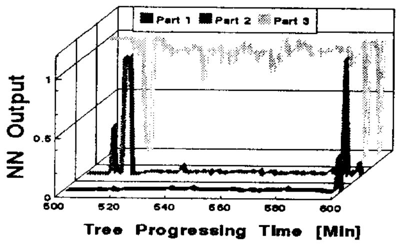

Fig. 3 Pattern recognition after neural network learning with 1.25-1.35 SFD

b) Case Study 2

The lifetime of insulation system has been designed to maintain very long safety area compared to the paper works. Almost of aging experiment depends upon ac-celeration test for analysis of aging processing. In this paper, we tried to apply different stress distinguished SFD, One example of recognition result represents fi-gure 5. In this case, the ratio of aging recognition can't be calculated like above section, because result has a many unknown point as complex damping characte-ristics. But result of ANN output cell was decided on above classification: safety area, middle area and dangerous area. Those area was supposed unknown area. Specially, test in a below SFD was easily cal-culated to the unknown area. Those characteristics was predicted on the unclear pattern between 0 and 1 for ANN discrimination, those results of bellow SFD test become widely more than high SFD learning data because of linear progress of tree.

Testing involved high SFD was calculated to much interested phenomena after safety area. At the first, the ambiguous results group both two output cell except other cell carry out some special region, those output is clear different error of the above section. Unstable area above the section called damping was discontinuous in medium aging time both two differ output, but unstable area in high SFD has a continuous value

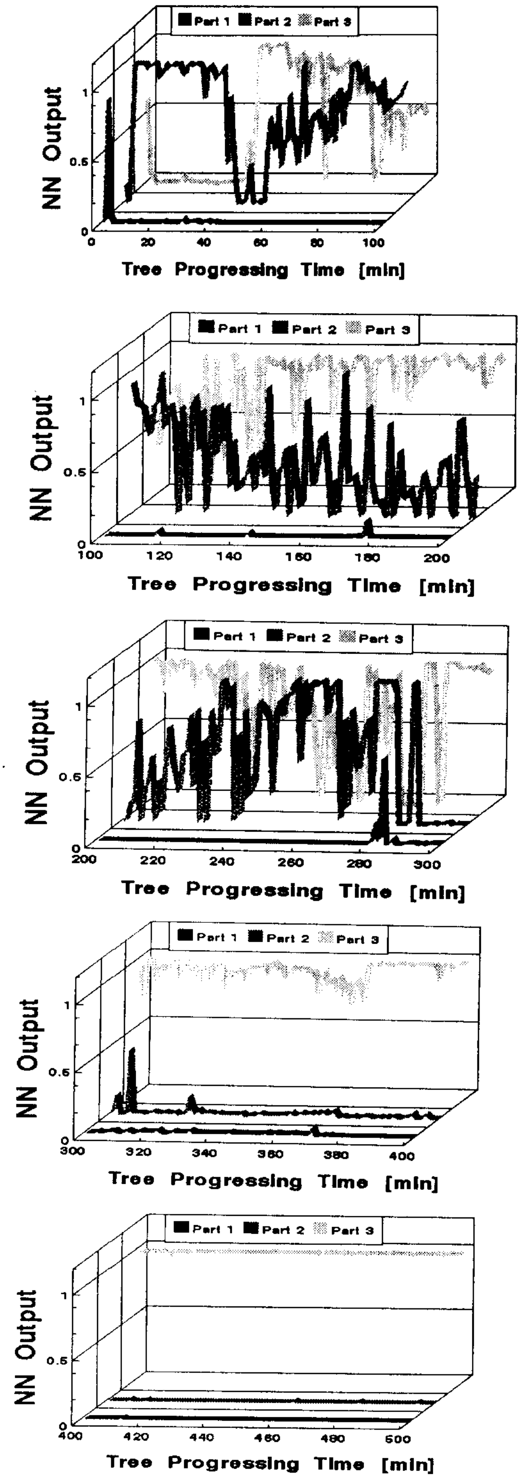

Fig. 4. Aging diagnosis test using neural network

between the safety and dangerous area, this result was estimated on the ANN characteristics which was possibilities as estimation of medium state.

At the second, the dangerous area was easily found to the recurrent phenomena of ANN output. However, such area is very difficult to analysis of mechanism and to predict the lifetime in present state, it is possible to discriminate via learning data accumulation.

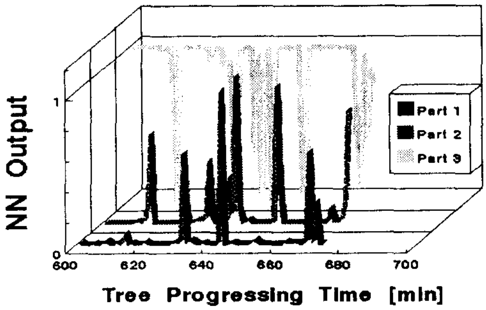

Fig. 4. Aging diagnosis test using neural network (continued)

6. Conclusion

A general outline of the development of neuro-fuzzy technique based PD diagnostics is given with emphasis on problems of the validity of underlying models and the interpretation of results. Some major ANN and FL based approaches are reviewed in this paper, with a discussion of certain problems that also are significant for modern approaches. After a discussion of primary PD events and resulting degradation, some basic mat-ters regarding measurement employing neuro-fuzzy techniques and testing are described and their problems are discussed. Examples in Figure 2. are given of the patterns obtained on some power apparatus and equip-ment and other sample models. These are necessarily selective and are intended to indicate how the tech-niques may be applied to acquisition of various discharges and to assessing of characteristic distribu-tion features of PD pattern. The methods include the new AI techniques integrated quantities, statistical system parameter and other fingerprints for recogni-zing the PD patterns within the power frequency cycle.

The New method called Semi-Fractal dimension has a good linearly characteristics and an ability of high speed calculation more than conventional Fractal dimen-sion. In our experiment, the construction of ANN consisting of 120 input cell for 3-d partial dis-charge has a possibility to compact size for PC or 1-chip processing system The New method called Semi-Fractal dimension has a good linearly characteristics and an ability of high speed calculation more than con-ventional Fractal dimension. In our experiment, the construction of ANN consisting of 120 input cell for 3-D partial discharge has a possibility to compact size for PC or 1-chip process.

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