Electric Power Systems Research 119 (2015) 100–110

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

# Improving pattern recognition accuracy of partial discharges by new data preprocessing methods

Mehrdad Majidi [a,*], Mohammad Oskuoee [b]

[a] Department of Electrical & Biomedical Engineering, University of Nevada, Reno (UNR), 1664 N. Virginia Street, Reno, NV 89557-0260, USA
[b] High Voltage Department, Niroo Research Institute (NRI), End of the Dadman Blvd, Shahrak Ghods, Tehran 1468617151, Iran

ARTICLE INFO

*Article history:*
Received 9 June 2014
Received in revised form 6 September 2014
Accepted 8 September 2014
Available online 26 September 2014

*Keywords:*
Signals norms
Pattern recognition
Partial discharges
ANN

ABSTRACT

In this paper, raw data of partial discharges (PDs) in solid, oil, and air insulation materials are measured experimentally in a high voltage laboratory for 18 samples. Then, three new methods for preprocessing the data based on first, second, and infinite signal norms and besides autocorrelation function (ACF) are proposed. Eventually, feed-forward back propagation (FFBP), radial basic function (RBF) neural networks, and neural network pattern recognition toolbox (nprtool) are used to recognize the patterns of the processed data. The results of the new methods are compared with phase resolved partial discharge (PRPD) method which is common in previous studies. Thanks to the new preprocessing methods, correlation factor in FFBP network, error value in RBF network, and classification percentage in nprtool become 0.9867, 0.0001 and 96.4%, respectively. Moreover, it is concluded that PDs process is a stationary random process which can be estimated by Gauss–Markov process.



## 1. Introduction

Electrical partial discharges (PDs) are localized dielectric failures in a small part of a solid or liquid electrical insulation system under high voltage stress, which do not bridge the space between two conductors. PD is a stochastic and nonlinear phenomenon [1,2]. It usually occurs in a void inside the insulation materials or on the surface and or around a high voltage conductor edge. When voltage and electrical stress exceed from insulation electrical strength, the probability of PD event will increase. On the other side, the oscillations and patterns of each type of PDs are different, which is helpful to discriminate the various PDs patterns. Several literatures studied different methods to recognize the PDs patterns. In [3], self organized map (SOM) neural network is used to investigate the PDs in XLPE cables and principle component analysis (PCA) is utilized for data reduction and preprocessing. In [4,5], PDs occurrence due to air bubbles inside the oil and between paper layers of the power transformers, is taken into consideration and ANN is used to detect the type of PDs resource. In [5], multi-sources of PDs in oil-impregnated papers are identified by phasor method and cluster analysis. In [2], some parameters of oil in a transformer bushing are examined via multilayer and radial neural network. The results show that radial neural network has the faster performance in comparison to multilayer network; however, it has less accuracy and reliability. In [6], PDs data in resin current transformers are evaluated and 92.5% recognition is achieved by FFBP neural network. In [7], PDs patterns in resin current transformers are discerned by means of extension neural network (ENN). Additionally, 3D patterns of PDs in the current transformers are extracted by conventional PRPD method. Furthermore, statistics parameters are calculated as the discriminative features to train the SOM neural network performing based on extensive distance rather than Euclidean distance [8]. In [9], PDs patterns are separated in solid materials by pulse shape characterization. Wavelet function and support vector machine (SVM) neural network are used as the feature extractor and classifier, respectively. In [10], PDs data in solid materials are processed with a phase window extraction method and afterward sequences of various neural networks such as FFBP are utilized to analyze the data. The performance of this method to distinguish the patterns is 83%. Classification and compression of PDs images and pattern recognition of PDs by self similarity effect is another technique to derive the features as the neural network inputs [11]. In Table 1, the neural networks and preprocessing methods used in previous studies are described briefly.

Main steps of PDs patterns recognition are mentioned as follows:

- Artificial defects creation in selected types of insulations.
- PDs measurement in laboratory.

* Corresponding author. Tel.: +1 775 772 4014.
*E-mail addresses:* mmajidi@unr.edu (M. Majidi), moskuoee@yahoo.com (M. Oskuoee).

http://dx.doi.org/10.1016/j.epsr.2014.09.014
0378-7796/

**Table 1**
Neural networks and preprocessing methods used in previous studies according with test conditions.

| Test condition | Neural network | Preprocessing method |
|---|---|---|
| On-line | SVM, SOM | Wavelet, PCA |
| Off-line | FFBP, RBF, probabilistic | Statistical parameters, image compressing of PDs, PRPD |

- Measured data preprocessing.
- Applying the output data from above step to various classifier tools such as ANNs and identifying the appropriate patterns.

In this paper, PDs pattern recognition accuracy is enhanced by applying some new preprocessing methods and different types of ANNs on the measured PDs data in solid, oil and air insulations. PDs were measured in a controlled and free noise condition in a high voltage laboratory. Although recognition rates in most previous works in this topic are close together and in an acceptable range (close to 95% and more), proposing some approaches for data compression and reduction of identification time are still appreciated [12]. In this paper, we propose a method in which data compression and feature extraction are performed in one step like extracting fractal features. Moreover, we increase number of discriminative features and decrease the volume of measured data to make the training process of neural networks easier and fast. Therefore, the identification time is reduced.

PD identification is usually performed using PRPD recognition. If the experimental setup is modified, the PRPD should not be affected. Therefore, our method which is based on PRPD patterns does not depend on electrical path between defect and measurement. As long as the measurement circuit records the impulses magnitudes and corresponding phase angles, it is not important whether a PD signal comes from a complicated set of transformer windings or from a simple capacitor [13]. So, our trained networks could identify the same type of PDs sources, mainly internal, surface and corona PDs, in other equipments such as cables and cable joints practically. However, objects with more number of voids with various sizes and also combination of different void sizes should be also taken into account in future to provide a database covering more probable defect conditions in real operation conditions.

Our main contributions beyond the alternative methods are as follows:

1. To our best knowledge, only 4–8 samples have been taken into consideration for PD pattern recognition in most previous works. Consequently, the reported recognition rates correspond with pattern recognition among the limited number of classes. However, we provide much more number of samples (18 samples) and reach 95% recognition rate for 17 samples thanks to new preprocessing methods.
2. In our second approach, we calculate the three norms of the $q_{mx}$, $q_{mn}$, and $q_n$ vectors extracted by just observing in each degree of each measured single cycle. However, in all PRPD methods, these vectors are extracted by observing in each window of several measured cycles. Although $q_{mx}$, $q_{mn}$, and $q_n$ vectors alone in each single cycle cannot be used for pattern recognition, nine discriminative features are extracted from each single measured cycle by the norm operators.
3. PD identification methods working based on stochastic analysis require minimum PD pulses in each cycle to be effective [14]. However, our proposed techniques do not suffer from this restriction and training features are extracted from random selected cycles.
4. Since ACF of one measured cycle does not have distinctive pattern, we propose a new compression method for PDs in sequential cycles to provide useful traces whose ACFs are meaningful and recognizable. In this respect, not only ACFs of compressed measured data for each PD type become discriminative, but also can be modeled by Gauss–Markov process.
5. We provide 18 samples including all main PD sources in such configurations that have not been examined yet in previous works. In this study, not only three main PD sources: internal, corona, and surface PDs are identified with an acceptable accuracy in solid, oil, air atmospheres, but also multiple source PDs (samples with more than one internal void) are recognized from single source PDs (samples with one internal void). Moreover, pattern recognition among the samples with same number of internal voids with a little difference in dimensions (0.5 mm difference) is achieved successfully.

The remainder of the paper is organized as follows. Section 2 describes the creation process of artificial defects and test samples. In Section 3, preprocessing methods to analyze the measured raw data are proposed. In Section 4, pattern recognition methods used to classify the extracted features from measured raw data are described. In Section 5, results and discussion are given and our conclusion is presented in Section 6.

## 2. Artificial defects creation

In this paper, surface PDs, internal PDs in solid and liquid insulations and corona in air are taken into account. Fifteen samples to study the internal PDs in the solid insulations with one, two, three, four, and five voids with 1, 1.5 and 2 mm dimensions were fabricated in accordance with Table 2. In addition, one sample to study the surface discharge, a case to examine the corona discharge in air and another one to explore the internal PDs in oil were defined, that provide the eighteen samples totally.

### 2.1. Test chamber and measurement devices

Most important parts of the test chamber are electrodes which must be clear from any PDs. Thus, a curve was made in the edge of electrodes by metal bronze according with Fig. 1; so that electrical field strength in these areas decreased to have a uniform electrical field in the space between two electrodes.

The radius and thickness of the plane electrode are 50 mm and 10 mm, respectively. Also, the tip radius and angle of the needle electrode are 50 μm and 20 degrees, respectively. The tests were performed in an atmosphere condition where the temperature, relative humidity, and pressure were 23 °C, 60%, and 643 mmHg, respectively.

**Table 2**
Created samples to investigate the internal PDs in solid insulations.

| Sample item | Number of voids | Voids dimension (mm) |
|---|---|---|
| 1 | 1 | 1 |
| 2 | 2 | 1 |
| 3 | 3 | 1 |
| 4 | 4 | 1 |
| 5 | 5 | 1 |
| 6 | 1 | 1.5 |
| 7 | 2 | 1.5 |
| 8 | 3 | 1.5 |
| 9 | 4 | 1.5 |
| 10 | 5 | 1.5 |
| 11 | 1 | 2 |
| 12 | 2 | 2 |
| 13 | 3 | 2 |
| 14 | 4 | 2 |
| 15 | 5 | 2 |