

# Analysis of Partial Discharge Source Using Artificial Neural Network

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**Abstract:** Partial Discharge (PD) patterns are an important tool for the diagnosis of High Voltage (HV) insulation systems. Human experts can discover possible insulation defects in various representations of the PD data. One of the most widely used representations is phase-resolved PD (PRPD) patterns. In order to ensure reliable operation of HV equipment, it is vital to relate the observable statistical characteristics of PDs to the properties of the defect and ultimately to determine the type of the defect. In this work, we have detected PD source using Artificial Neural Network (ANN) tool in Matlab software.

**Keywords:** Partial Discharge, Artificial Neural Network, Phase- Resolved, Statistical parameters.

## I. INTRODUCTION

PD is a localized electrical discharge that partially bridges the insulation between conductors and which may or may not occur adjacent to a conductor [1]. In general, PDs are concerned with dielectric materials used and partially bridging the electrodes between which the voltage is applied. The insulation may consist of solid, liquid, gaseous materials or any combination of these. PD is the main reason for the electrical ageing and insulation breakdown of HV electrical apparatus. Different sources of PD give different effect on insulation performance. Therefore, PD classification is important in order to evaluate the harmfulness of the discharge [2].

PD classification aims at the recognition of discharges of unknown origin. For many years, the process was performed by investigating the pattern of the discharge using the well known ellipse on an oscilloscope screen, which was observed crudely by eye. Nowadays, there has been extensive published research to identify PD sources by using intelligent technique like artificial neural networks, fuzzy logic and acoustic emission [2].

The recent upsurge of research on PD phenomena has been driven in part by development of new fast digital and computer-based techniques that can process and analyse signals derived from PD measurements. There seems to be an expectation that, with sufficiently sophisticated digital processing techniques, it should be possible not only to gain new insight into the physical and chemical basis of PD phenomena but also to define PD 'patterns' that can be used for identifying the characteristics of the insulation 'defects' at which the observed PD occur [3]. One of the undoubted advantages of a computer-aided measuring system is the ability to process a large amount of information and to transform this information into an understandable output [4].

There are many types of patterns that can be used for PD source identification. If these differences can be presented in terms of statistical parameters, identification of the defect type from the observed PD pattern may be possible. As each defect has its own particular degradation mechanism, it is important to know the correlation between discharge patterns and the kind of defect. Therefore, progress in the recognition of internal discharge and their correlation with the kind of defect is becoming increasingly important in the quality control in insulating systems [4]. Research has been carried out in recognition of PD sources using statistical techniques and neural network. We present a method for the automated recognition of PRPD patterns using an ANN for the actual classification task [8]. In our present work, initial step is pre-processing of data using Statistical parameters like mean, standard deviation, variance, skewness and kurtosis and a rough draft is made about PD source. The back propagation algorithm is used for accurate detection of PD source using 'nntool' available in MATLAB.

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## II. PD DATA PATTERNS AND SYSTEM MODEL

There are three different types of data patterns currently used for the analysis and evaluation of PD. These are: phase-resolved data, time-resolved data and data without phase/time information. These types are discussed in following sections. These parameters are given as an input to the system as shown in fig.1.

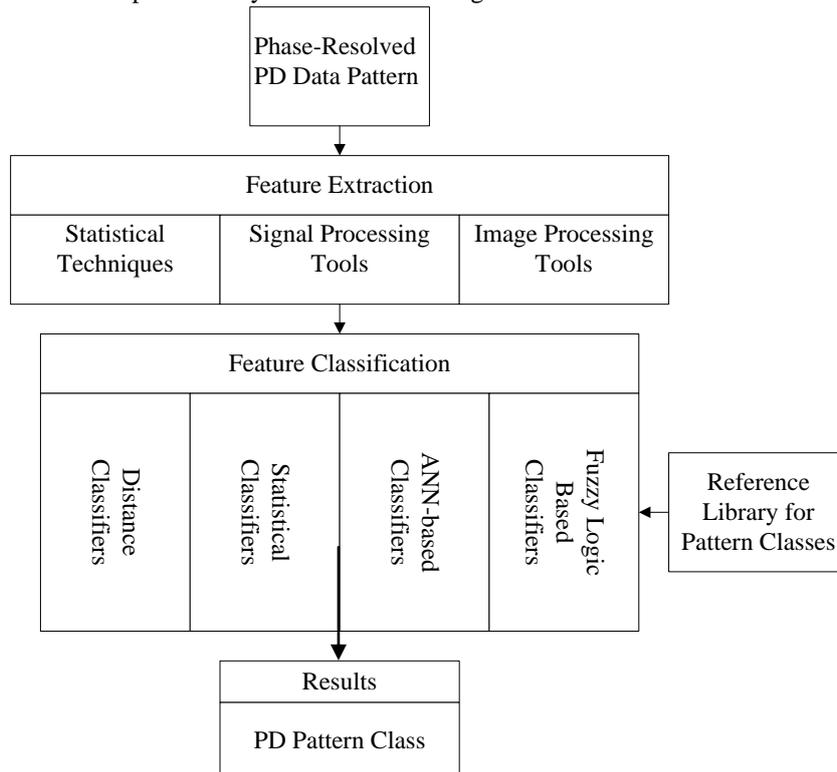


Fig.1. System model for PD Classification using phase-resolved data patterns

### II.I. Phase Resolved Data Patterns

These PD data are obtained in relation to the waveform of the alternating current (AC) test voltage. The test voltage is assumed to be held constant and the voltage phase angle is divided into a suitable number of small bins or windows. The digital PD detector is used for acquisition of all the individual quasi-integrated pulses and quantifying each of these PD pulses by their discharge magnitude ( $q$ ), the corresponding phase angle or discharge epoch ( $\phi$ ) at which they occur and their number densities or discharge rates ( $n$ ) over chosen interval of time. The analysis software plots these data either as univariate distributions (functions of the phase positions  $\phi$ ) or as a bivariate distribution (such as  $\phi \sim q \sim n$  plots). The most commonly used univariate distributions are:

- $(qa \sim \phi)$  : average charge in each phase window vs.  $\phi$
- $(qp \sim \phi)$  : peak charge for each phase window vs.  $\phi$
- $(n \sim \phi)$  : number of PD pulses detected in each phase window vs.  $\phi$

The bivariate distribution data, i.e.,  $\phi \sim q \sim n$  patterns, is generally viewed as a three-dimensional (3D) plot/image. This 3D plot is regarded as one of the more complete forms of graphical representation of a PD pulse distribution. The PD pulse height distribution (PDHD) or pulse amplitude histogram (PAH) is the distribution of pulse number ( $n$ ) vs. pulse amplitude ( $q$ ) which can be either derived indirectly from the  $\phi \sim q \sim n$  plots or obtained directly by measurement [12].

### II.II. Time Resolved Data Patterns

In phase-resolved data, there is no information regarding true shapes of the discharge pulses. In contrast, the time-resolved data pattern, i.e.,  $q \sim t$  data, displays the true shapes of the individual PD pulses. Again, the test voltage is treated as a constant. This data pattern has attractive advantages since there exist direct relationship between the physics of the defect

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and the shape of the PD signal; also the measurement procedure involves the use of less expensive instrumentation than that required for phase-resolved measurements. Aging of insulating materials can be readily observed from these data patterns.

### II.III. Data without Phase/Time Information

A typical example of PD pulse data in which phase-time information is absent is that of ( $q \sim V$ ) which is obtained by measurement of discharge magnitude at varying amplitudes of test voltage so as to demonstrate the PD hysteresis effect in a test cycle. The observed hysteresis effect follows directly from the fact that a lower applied voltage is necessary to sustain a discharge process once it has been initiated [7].

### III. FEATURE EXTRACTION

There are quite a good number of classifiers available in the literature for pattern recognition. The various approaches are based on: decision functions, distance functions, likelihood functions, artificial neural networks, trainable classifiers etc. All the different classifiers proposed for PD may be grouped as distance classifiers, statistical classifiers, ANN-based classifiers and fuzzy logic based classifiers [9]. As shown in fig.1, after obtaining the PD parameters, the next step is to apply feature extraction on input data. Any pattern which can be recognized and classified possesses a number of discriminatory attributes or features. Thus, the first step in any recognition process is to consider the problem of what discriminatory features to select and how to extract these features from the patterns. The tools used for selection of feature vector (a set of selected features) are generally application dependant. Over the past couple of decades, several different approaches have been adopted for the choice of features in PD pattern recognition. These different approaches can be broadly grouped into the following methods/tools, i.e., statistical methods, pulse shape parameter approach, signal processing tools, image processing tools and time-series approach [8].

### IV. STATISTICAL PARAMETERS

As shown in fig.1, there are various methods available for feature extraction. In present work, statistical techniques are used for input processing and feature extraction. The important parameters to characterize PDs are phase angle ' $\phi$ ', PD charge magnitude ' $q$ ' and PD number of pulses ' $n$ '. PD distribution patterns are composed of these three parameters. Statistical parameters are obtained for phase resolved pattern ( $n-q$ ).

#### IV.I. Processing of Data ( $\phi, q$ and $n$ )

The cyclic readings at the point of discharge process are collected for ' $n$ ', ' $\phi$ ', ' $q$ ' and corresponding voltage ' $V$ ' values. The readings collected are processed with respect to statistical parameters to obtain objective values. These obtained values are further used to diagnose the most likely source of PD. The processing is described below in Fig. 2.

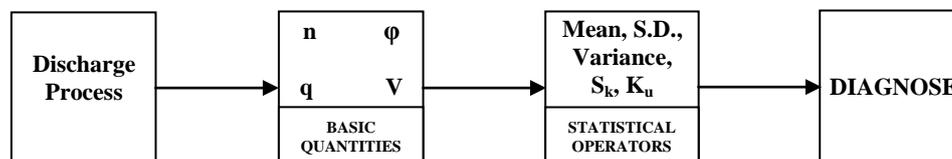


Fig.2. Block Diagram of discharge analysis using statistical parameters

In the fig.2, S.D. represents Standard Deviation,  $S_k$  represents Skewness and  $K_u$  represents Kurtosis. Statistical analysis is applied for the computation of several statistical operators. The definitions of most of these statistical operators are described below. The profile of all these discrete distribution functions can be put in a general function, i.e.,  $y_i=f(x_i)$ . The statistical operators can be computed as follows:

$$\text{Mean Value: } (\mu) = \frac{\sum_{i=1}^N (x_i) f(x_i)}{\sum_{i=1}^N f(x_i)} \quad \dots\dots\dots(\text{eq. 1})$$

$$\text{Variance: } (\sigma^2) = \frac{\sum_{i=1}^N (x_i - \mu)^2 f(x_i)}{\sum_{i=1}^N f(x_i)} \quad \dots\dots\dots(\text{eq. 2})$$

$$\text{Skewness } (S_k) = \frac{\sum_{i=1}^N (x_i - \mu)^3 f(x_i)}{\sigma^3 \sum_{i=1}^N f(x_i)} \quad \dots\dots\dots(\text{eq. 3})$$

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$$\text{Kurtosis: } (K_u) = \frac{\sum_{i=1}^N (x_i - \mu)^4 f(x_i)}{\sigma^4 \sum_{i=1}^N f(x_i)} - 3 \quad \dots\dots\dots(\text{eq. 4})$$

$$\text{Standard Deviation} = \sqrt{\text{Variance}} \quad \dots\dots\dots(\text{eq. 5})$$

where,

- x = number of pulses n,
- f(x) = PD charge magnitude q,
- μ = average mean value of PD charge magnitude q,
- σ = variance of PD charge magnitude q

Skewness and Kurtosis are evaluated with respect to a reference normal distribution. Skewness is a measure of asymmetry or degree of tilt of the data with respect to normal distribution. If the distribution is symmetric, Sk=0; if it is asymmetric to the left, Sk>0; and if it is asymmetric to the right, Sk<0. Kurtosis is an indicator of sharpness of distribution. If the distribution has the same sharpness as a normal distribution, then Ku=0. If it is sharper than normal, Ku>0, if it is flatter, Ku<0 [5] [6].

## V. DATA PROCESSING USING ANN

ANN is effective going to be effective, the training dataset must be complete enough to satisfy the following goals:

- Every group must be represented: The training dataset consists of several subgroups, each having its own central tendency toward a particular pattern. All of these patterns must be represented.
- Within each class, statistical variation must be adequately represented: The range of data presented to the ANN must represent the entire range of data with noise included. In certain cases, only lower and upper bound data with few scattered data points in between the range will be available. In that case, it is acceptable to have a sparse dataset.

### V.I Artificial Neural Network

Recently, the application of ANN to the recognition of PD sources is gaining importance and new research field aiming at diagnosis of HV insulation. Just as mankind was learning and developing by means of thousands of trials, errors and improvements from the errors, ANN also provide brain-like capabilities for solving problems, they learn by examples. ANN basically belongs to ‘nonparametric’ methods. This means that usually it is not necessary to make any assumptions about data structure. In statistics various preliminary conditions, e.g. data from normal populations, must be fulfilled in order to carry out the analysis. The problem to be dealt with here is to assign ‘unknown’ PD patterns to known ones. Today, the most widely used learning algorithm in ANN for such classification purposes is the back-propagation algorithm [9][10].

Generally the structure of ANN is based on a three-layer system: input layer, hidden layer(s) and output layer. Basically, the inner layer may have several input neurons or processing elements and is driven by the data obtained by the PD measuring system. Then, the hidden layer characterizes the typical structure of the ANN and differs for diverse NN. Finally, the outer layer is defined according to user expectancies and can be represented by one or more processing element.

### V.II Back Propagation Algorithm based ANN

This type of the ANN received its name from how it handles errors i.e. difference between estimated value and expected value. It consists of the input layer, at least one hidden layer and the output layer, Figure below. Each layer is fully connected to the succeeding layer. The main purpose of the HL is to extract features of the different PD sources and pass its knowledge to the output layer (or succeeding hidden layer if there are more than one hidden layers). The number of processing elements in the input layer is in our case equal to the number of the statistical operators. The number of neurons in the output layer is equal to the number of defects to be classified. The number of output neurons in the hidden layer is usually between the number of elements in the input and the output layer. However, it tends to be larger for more complex problems.

### V.III Importing Data

In initial step, pre-processing of data is carried out using Statistical parameters like mean, standard deviation, variance, skewness and kurtosis and a rough draft is made about PD source. For accurate detection of PD source, nntool is used using MATLAB, the following GUI (Graphical User Interface) or nntool window appears as shown in fig.3.

Input data i.e. statistical parameters are imported in column INPUT DATA and targets which are decided by the user are imported in column TARGET DATA. The input parameters are

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- P1 = Known data which are void, surface and corona having parameters such as mean, standard deviation, variance, skewness and kurtosis.
- pp 1 cycles = Unknown data1 having parameters such as mean, standard deviation, variance, skewness and kurtosis.
- pp 2 cycles = Unknown data2 having parameters such as mean, standard deviation, variance, skewness and kurtosis.
- pp 3 cycles = Unknown data3 having parameters such as mean, standard deviation, variance, skewness and kurtosis.
- p1 cycles = Unknown data2007 having parameters such as mean, standard deviation, variance, skewness and kurtosis.
- p2 cycles = Unknown data2011 having parameters such as mean, standard deviation, variance, skewness and kurtosis.

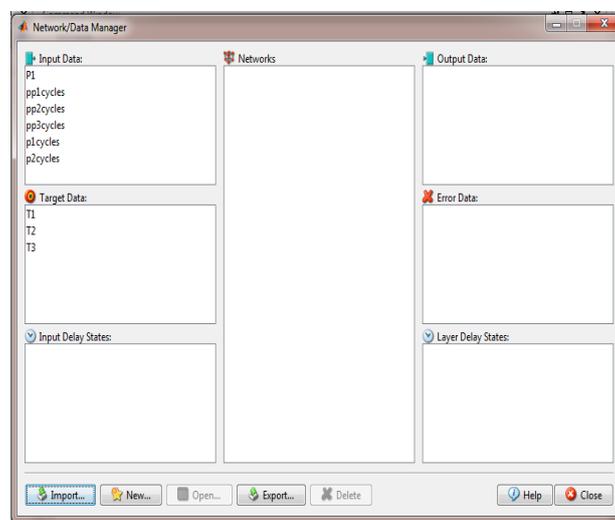


Fig. 3. Network/Data Manager Window to define 'Input data' and 'Target data'

As shown in fig.3. targets T1, T2, and T3 are created for Surface, Corona and Void. These three targets are defined as below

- T1 = Own targets are decided [50, 60, 70].
- T2 = Own targets are decided [60, 70, 50].
- T3 = Own targets are decided [70, 50, 60].

The three values 50, 60 and 70 represent Surface, Corona and Void respectively for target T1. Similarly, values 60, 70, 50 for target T2 and 70, 50, 60 for target T3 represent Surface, Corona and Void respectively.

### V.IV Creating New Network

Larger ANNs require large training datasets in order to obtain most accurate results. Over fitting is most likely when the model is large. While designing a ANN and selecting the training dataset for a given problem, the designer has to explore answers for the following questions:

- Are there any transformations required for the training dataset?
- Are there enough sample representations in all sub-classes?
- How many ANN architecture layers are needed? (two layers, three layer or more layered network)
- How many hidden neurons?
- What type of transfer functions to be used?
- How long is training required for the network?

In present work, we have implemented three layered neural networks with one layer for input, hidden and output each.

### V.V Training

Once a network has been structured for a particular application, that network is ready to be trained. To start this process the initial weights are chosen randomly. In next step, the ANN training/learning began with initial weights and self-adjustment of these weights. There are two approaches to training - supervised and unsupervised.

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- Supervised training involves a mechanism of providing the network with the desired output either by manually "grading" the network's performance or by providing the desired outputs with the inputs.
- Unsupervised training is where the network has to make sense of the inputs without external help.

The vast bulk of networks utilize supervised training. Unsupervised training is used to perform some initial characterization on inputs. However, in the full blown sense of being truly self learning, it is still just a shining promise that is not fully understood, does not completely work, and thus is relegated to the lab.

## V.VI Simulation

After the ANNclassifier has been trained and has produced a set of best weights and biases, the next step is to determine how accurate the resulting model (where model means the ANN with the set of best weights, sufficient number of layers and appropriate number of neurons) is on the test data. Although measures such as sum of squared deviations or cross-entropy error can be used, a reasonable measure of accuracy is simply the percentage of correct predictions made by the model.

## V.VII Output

Classification with neural networks is an important, fascinating and complex topic. The random initialization of network weights prior to each execution of the ANN training algorithm can in some cases cause final classification results to vary from execution to execution, even when all other factors (e.g., training data, learning rate, momentum, network topology) are kept constant. Particularly when working with very limited training datasets, the variation in results can be large. Under such circumstances, it is best to expand training data on the basis of improved ground truth. If this is not possible, generation of optimum results can sometimes be made through combination of the results of multiple ANN classifications. The simulated output for given input data set is obtained to be 59.9192.

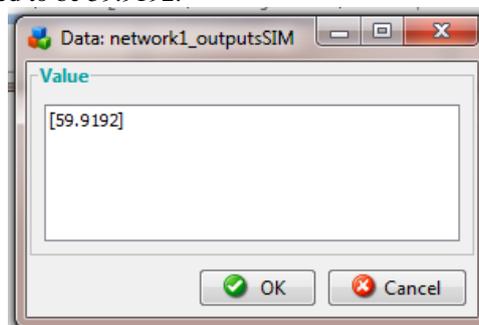


Fig.4. Output Window showing output numerical value obtained after simulation

## VI. RESULT AND DISCUSSION

As shown in system model in fig.1 the last step is result and classification. After analysis we obtained the results and are summarized in table 1 and table 2. Table 1 indicates the value of all statistical parameters such as mean, standard deviation, variance, skewness and kurtosis against known value of void, surface and corona discharges. Whereas Table 2 indicates the value of all statistical parameters against data1, data2 and data3 which is the unknown data whose discharge we have determined by using the reference of Table 1. The output obtained after the simulation and execution process is 59.9192 which is approximately close to the value of surface discharge of target 'T2'. Hence, it can be concluded that data1 is surface discharge. Similarly, the simulated results are obtained for other unknown PD data. Analysis involves determining unknown PD patterns by comparing those with known PD patterns such as void, surface and corona. The comparison is done with respect to their statistical parameters [7] [11] [12].

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Table 1. Parameters of known PD patterns

Sr. No.	Parameters	Void	Surface	Corona
1	Mean	13320.32	145.706	1.426
2	Standard deviation	7553.716	126.009	1.139
3	Variance	$1.64 * 10^8$	17921.01	2.279
4	Skewness	$3.66 * 10^{-17}$	0.809	0.26
5	Kurtosis	0.04878	2.442	0.966

Table 2. Parameters of unknown PD Patterns

Sr. No.	Parameters	data1	data2	data3
1	Mean	105.119	553.93	13320.32
2	Standard deviation	97.966	698.3	7553.716
3	Variance	16714.23	$4.94 * 10^5$	$1.64 * 10^8$
4	Skewness	0.692	1.939	$-3.7 * 10^{-17}$
5	Kurtosis	2.004	6.31	0.04878

The following observations are made from the results. The analysis done from statistical parameters indicates that data1 is surface discharge, data2 is surface discharge and data3 is void discharge. The analysis using statistical parameters can be done for various types of PD discharges [7]. Table 3 indicates the value of PD source for the unknown data by using neural network.

Table 3. Outputs obtained from ANN for given unknown data

Sr. No.	Unknown data (Input)	PD Source (Output)
1	data1	Surface
2	data2	Void/surface
3	data3	Void
4	data2007	Void
5	data2011	Void/surface

## VII. CONCLUSION

From statistical parameters, the PD source cannot be concluded accurately so it needs to be applied to other classification methods such as neural network, Fuzzy logic etc. as a pre-processing parameters for getting accurate PD source. The ANN on execution produce the dual results for data2 and data2011 indicating the need for more input samples in training data set. From the present work, we can make observe that PD source can be classified using the phase resolved pattern as the input. It is also possible to detect multiple sources of breakdown those exist in insulation along with determining exact percentage of that source ANN. The use of back-propagation algorithm is better choice for training ANN as it performs optimization of the weights by first propagating the input signal forward, then propagating the calculated error backwards to make adjustment to the initial weights. In future work we aim at developing ANN trained using methods other than back propagation.

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