Analysis and Determination of Partial Discharge Type using Statistical Techniques and Back Propagation Method of Artificial Neural Network for Phase-Resolved Data

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***Abstract* : -Partial discharge (PD) patterns are significant 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 crucial to relate the observable statistical characteristics of PDs to the properties of the defect and ultimately to determine the type of the defect. In present work, we have obtained and analysed combined use of PRPD patterns (φ-q), (φ-n) and (n-q) using statistical parameters such as skewness and kurtosis for two patterns viz. (φ-q) and (φ-n) along with mean, standard deviation, variance, skewness and kurtosis for (n-q) to detect type of PD and we have verified the obtained results by providing obtained statistical parameters as an input for training of artificial neural network (ANN) in MATLAB tools.**

Keywords - Partial Discharge, Phase-resolved, Statistical parameters, Artificial Neural Network.

1. 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, or gaseous materials, or any combination of them. PD is the main reason for the electrical ageing and insulation breakdown of high voltage 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 analyze 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 [4]. 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 [5]. Research has been carried out in recognition of partial discharge sources using statistical techniques and neural network [6]. We present a method for the automated recognition of PRPD patterns using an ANN for the actual classification task [12]. In our study, we have tested various internal and external discharges like void, surface and corona using statistical parameters such as skewness and kurtosis for (φ-q) and (φ-n) and mean, standard deviation, variance, skewness and kurtosis for (n-q) as a initial step known as pre-processing and a rough draft is made about the results of PD Type and verified the results by using back propagation method of Artificial Neural Network in MATLAB software.

2. STATISTICAL PARAMETERS

The important parameters to characterize PDs are phase angle φ, 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 patterns (φ-q), (φ-n) and (n-q).

2.1. Processing of data

The data to be processed obtained from generator includes φ, q, n and voltage V. From this data, phase resolved patterns are obtained.

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2.1.1. Analysis of Phase-Resolved (φ-q) and (φ-n) using Statistical Techniques

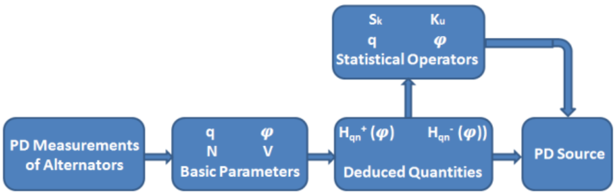

Fig.1 (a). Block diagram of discharge analysis for (φ-q)

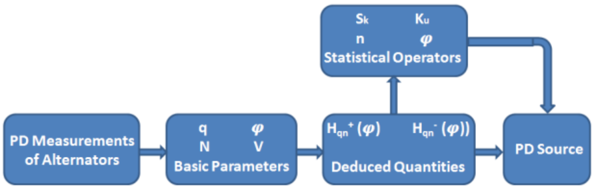

Fig.1 (b). Block diagram of discharge analysis for (φ-n)

PD pulses are grouped by their phase angle with respect to 50 (± 5) Hz sine wave. Consequently, the voltage cycle is divided into phase windows representing the phase angle axis (0 to 360'). If the observations are made for several voltage cycles, the statistical distribution of individual PD events can be determined in each phase window. The mean values of these statistical distributions results in two dimensional patterns of the observed PD patterns throughout the whole phase angle axis [6]. A two-dimensional (2-D) distribution φ-q and φ-n represents PD charge magnitude 'q' and PD number of pulses 'n' as a function of the phase angle 'φ' [3].

The mean pulse height distribution $H_{qn}(\varphi)$ is the average PD charge magnitude in each window as a function of the phase angle φ. The pulse count distribution $H_n(\varphi)$ is the number of PD pulses in each window as a function of phase angle φ. These two quantity are further divided into two separate distributions of the negative and positive half cycle resulting in four different distributions to appear: for the positive half of the voltage cycle $H_{qn}^{+}(\varphi)$ and $H_n^{+}(\varphi)$ and for the negative half of the voltage cycle $H_{qn}^{-}(\varphi)$ and $H_n^{-}(\varphi)$ [5]. For a single defect, PD quantities can be described by the normal distribution. The distribution profiles of $H_{qn}(\varphi)$ and $H_n(\varphi)$ have been modeled by the moments of the normal distribution: skewness and kurtosis.

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

$$\text{Kurtosis: } (K_u) = \frac{\sum_{i=1}^{N}(x_i-\mu)^4 f(x_i)}{\sigma^4 \sum_{i=1}^{N} f(x_i)} - 3 \quad \dots\dots\dots (2)$$

where,
f(x) = PD charge magnitude q,
μ = average mean value of q,
σ = variance of 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 same sharpness as a normal distribution, then Ku=0. If it is sharper than normal, Ku>0, and if it is flatter, Ku<0 [3] [7].

2.1.2. Analysis of Phase-Resolved (q-n) using Statistical Techniques

Fig. 2. Block diagram of discharge analysis for (n-q)

Where,
S.D = standard deviation
Sk = skewness
Ku = 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:

$$\text{Mean Value: } (\mu) = \frac{\sum_{i=1}^{N}(x_i)\, f(x_i)}{\sum_{i=1}^{N} f(x_i)} \quad \dots\dots\dots (3)$$

$$\text{Variance: } (\sigma^2) = \frac{\sum_{i=1}^{N}(x_i-\mu)^2 f(x_i)}{\sum_{i=1}^{N} f(x_i)} \quad \dots\dots\dots (4)$$

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

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 same sharpness as a normal distribution, then Ku=0. If it is sharper than normal, Ku>0, and if it is flatter, Ku<0 [3] [8].

3. RESULTS AND DISCUSSION OF STATISTICAL PARAMETERS

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 [9] [10][11].

3.1. Analysis for (φ-q)

The phase resolved patterns are divided into two types: (φ-q) and (φ-n). The phase resolved patterns (φ-q) are obtained for three known PD patterns: void, surface and corona (as

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discussed in 3.1.1) and three unknown PD patterns: data1, data2 and data3 (as discussed in 3.1.3) [9]

3.1.1. 2-D distribution of (φ-q) for known PD patterns

Fig.3 (a), Fig.3 (b) and Fig.3 (c) are the phase φ vs. charge q plot for void, surface and corona discharges respectively.

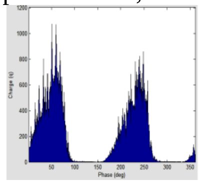

Fig.3(a).Phase plot (φ-q) of void discharge

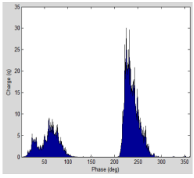

Fig.3(b).Phase plot (φ-q) of surface discharge

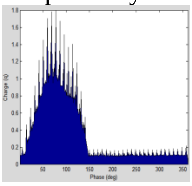

Fig.3(c). Phase plot (φ-q) of corona discharge

3.1.2. Parameters of known PD patterns

TABLE I. PARAMETERS OF KNOWN PD PATTERNS

Parameter	Void	surface	corona
Skewness H_{qn}^{+} (φ)	1.0013	1.2134	0.3555
Skewness H_{qn}^{-} (φ)	0.9901	1.8219	1.3659
Kurtosis H_{qn}^{+} (φ)	2.9046	3.6064	2.4354
Kurtosis H_{qn}^{-} (φ)	2.7872	5.4506	7.5947

3.1.3. 2-D distribution of (φ-q) for unknown PD patterns

Fig.4 (a), Fig.4 (b) and Fig.4 (c) are the phase φ vs. charge q plot for data1, data2 and data3 respectively.

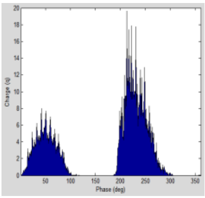

Fig.4 (a) Phase plot (φ-q) of data1

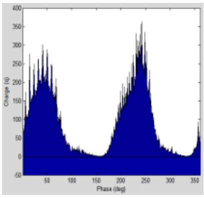

Fig.4 (b) Phase plot (φ-q) of data2

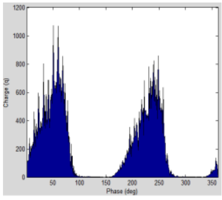

Fig.4 (c) Phase plot (φ-q) of data3

From Fig.4 (a), it is seen that the following plot is similar to void and surface discharge. Fig.4 (b), is also similar to void and surface discharge and Fig.4(c), is similar to void discharge.

3.1.4. Parameters of unknown PD Patterns

TABLE II. PARAMETERS OF UNKNOWN PD PATTERNS

Parameter	data1	data2	data3
Skewness H_{qn}^{+} (φ)	0.8991	0.7456	1.0013
Skewness H_{qn}^{-} (φ)	1.1833	0.8509	0.9901
Kurtosis H_{qn}^{+} (φ)	2.5719	2.1814	2.9046
Kurtosis H_{qn}^{-} (φ)	3.7467	2.6512	2.7872

3.2. Analysis for (φ-n)

The phase resolved (φ-n) patterns consist of three known PD patterns: void, surface and corona (as discussed in 3.2.1) and three unknown PD patterns: data1, data2 and data3 (as discussed in 3.2.3) [9]. The plots are discussed below:

3.2.1 Phase resolved plot (φ-n) of known PD patterns

Fig.5 (a), Fig.5 (b) and Fig.5 (c) are the phase φ vs. number of pulses n for void, surface and corona discharges respectively.

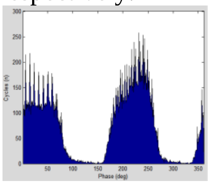

Fig.5(a).Phase plot (φ-n) of void discharge

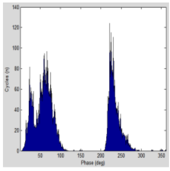

Fig.5(b).Phase plot (φ-n) of surface discharge

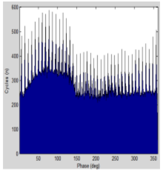

Fig.5(c).Phase plot (φ-n) of corona discharge

3.2.2. Parameters of unknown PD Patterns

TABLE III. PARAMETERS OF KNOWN PD PATTERNS

Parameter	Void	surface	corona
Skewness H_{n}^{+} (φ)	0.4954	1.0082	1.3942
Skewness H_{n}^{-} (φ)	0.4329	2.3686	1.3798
Kurtosis H_{n}^{+} (φ)	2.0535	2.871	4.8337
Kurtosis H_{n}^{-} (φ)	1.9137	8.4788	7.3215

3.2.3. Phase resolved plot (φ-n) of unknown PD patterns

Fig.6 (a), Fig.6 (b) and Fig.6 (c) are the phase φ vs. number of pulses n plot for data1, data2 and data3 respectively.

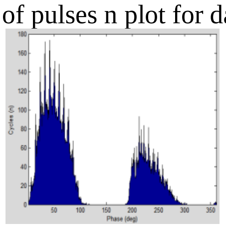

Fig.6(a).Phase plot (φ-n) of data1

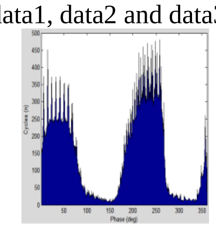

Fig.6(b).Phase plot (φ-n) of data2

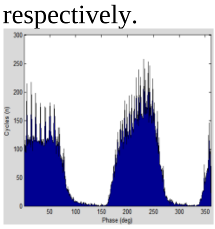

Fig.6(c).Phase plot (φ-n) of data3

From Fig.6 (a), it is seen that the following plot is similar to void and surface discharge. Fig.6 (b), is similar to void discharge and Fig.6 (c), is also similar to void discharge

3.2.4. Parameters of unknown PD patterns

TABLE IV. PARAMETERS OF UNKNOWN PD PATTERNS

Parameter	data1	data2	data3
Skewness H_{n}^{+} (φ)	0.8016	0.574	0.4954
Skewness H_{n}^{-} (φ)	1.0169	0.42	0.4329
Kurtosis H_{n}^{+} (φ)	2.3724	2.1091	2.0535
Kurtosis H_{n}^{-} (φ)	3.2011	1.8003	1.9137

3.3. Analysis for (n-q)

The phase resolved patterns n-q are obtained for three known PD patterns: void, surface and corona (as discussed in 3.3.1) and three unknown PD patterns: data1, data2 and data3 (as discussed in 3.3.3) [10].

3.3.1. 2-D distribution of n-q for known PD patterns

Fig. 7(a), Fig. 7(b), Fig. 7(c), Fig. 7(d) and Fig. 7(e) are the n-q plot of mean, standard deviation, variance, skewness and kurtosis for void discharge respectively.

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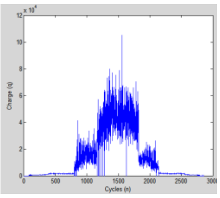

Fig.7(a).Mean plot (n-q) of void discharge

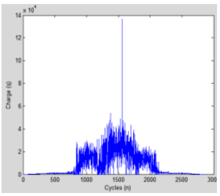

Fig.7(b).Standard deviation plot (n-q) of void discharge

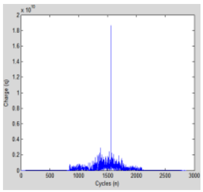

Fig.7(c).Variance plot (n-q) of void discharge

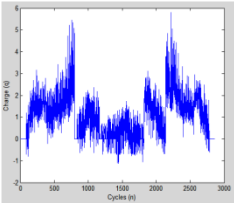

Fig.7 (d) Skewness plot (n-q) of void discharge

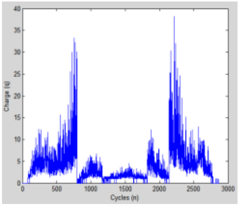

Fig.7 (e) Kurtosis plot (n-q) of void discharge

Referring to Fig. 7 (a), Fig. 7 (b) and Fig. 7 (c) of void discharge, it can be seen there is a peak occurring somewhere after 1500 cycle, which is a void discharge and in Fig. 7 (d) and Fig. 7 (e) of skewness and kurtosis, the value decreases at that cycle where peak occurs.

Fig. 8(a), Fig. 8(b), Fig. 8(c), Fig. 8(d) and Fig. 8(e) are the n-q plot of mean, standard deviation, variance, skewness and kurtosis for surface discharge respectively.

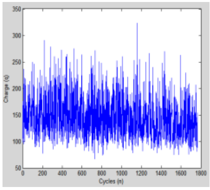

Fig.8 (a) Mean plot (n-q) of surface discharge

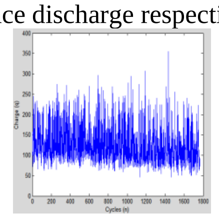

Fig.8 (b) Standard deviation plot (n-q) of surface discharge

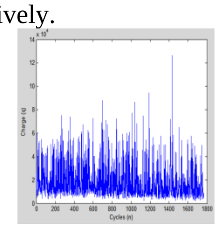

Fig.8 (c) Variance plot (n-q) of surface discharge

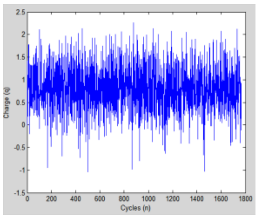

Fig.8 (d) Skewness plot (n-q) of surface discharge

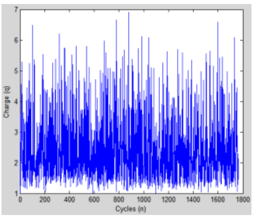

Fig.8 (e) Kurtosis plot (n-q) of surface discharge

In surface discharge, charges are distributed uniformly over all cycles for mean, standard deviation, variance, skewness and kurtosis as shown in Fig. 8(a), Fig. 8(b), Fig. 8(c), Fig. 8(d) and Fig. 8(e).
Fig. 9(a), Fig. 9(b), Fig. 9(c), Fig. 9(d) and Fig. 9(e) are the n-q plot of mean, standard deviation, variance, skewness and kurtosis for corona discharge respectively.

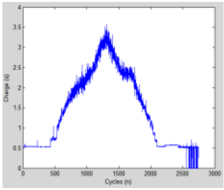

Fig.9 (a) Mean plot (n-q) of corona discharge

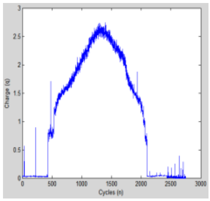

Fig.9 (b) Standard deviation (n-q) of corona discharge

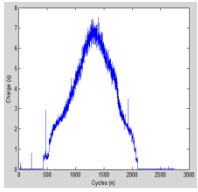

Fig.9 (c) Variance plot (n-q) of corona discharge

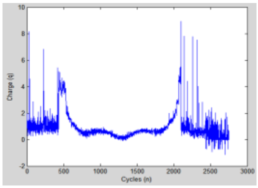

Fig.9 (d) Skewness plot (n-q) of corona discharge

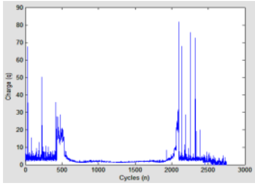

Fig.9 (e) Kurtosis plot (n-q) of corona discharge

Referring to Fig. 9(a), Fig. 9(b) and Fig. 9(c) of corona discharge, it can be seen the charges starts occurring after 500 cycle increasing somewhere upto 1200 cycle and then decreasing after 2000 cycle, and in Fig. 9(d) and Fig. 9(e) of skewness and kurtosis, the value decreases from 500 cycle till 2000 cycle.

3.3.2. Parameters of known PD patterns

TABLE V. PARAMETERS OF KNOWN PD PATTERNS

Parameters	Void	Surface	Corona
Mean	13320.32	145.706	1.426
Standard deviation	7553.716	126.009	1.139
Variance	$1.64*10^{8}$	17921.01	2.279
Skewness	$3.66*10^{-17}$	0.809	0.26
Kurtosis	0.04878	2.442	0.966

3.3.3. 2-D distribution of (n-q) for unknown PD patterns

Fig. 10(a), Fig. 10(b), Fig. 10(c), Fig. 10(d) and Fig. 10(e) are the n-q plot of mean, standard deviation, variance, skewness and kurtosis for data1 respectively.

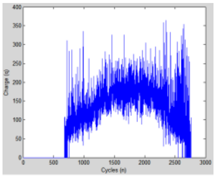

Fig.10 (a) Mean plot (n-q) of data1

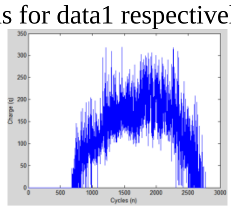

Fig.10 (b) Standard deviation plot (n-q) of data1

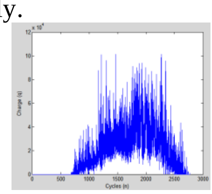

Fig.10 (c) Variance plot (n-q) of data1

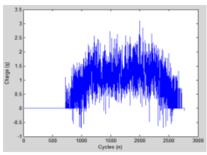

Fig.10 (d) Skewness plot (n-q) of data1

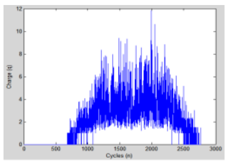

Fig.10 (e) Kurtosis plot (n-q) of data1

In Fig. 10(a), Fig. 10(b), Fig. 10(c), Fig. 10(d) and Fig. 10(e), the charges are uniformly distributed similar to surface discharge. Hence, it can be concluded that data1 is having

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surface discharge. Fig. 11(a), Fig.11(b), Fig. 11(c), Fig. 11(d) and Fig. 11(e) are the n-q plot of mean, standard deviation, variance, skewness and kurtosis for data2 respectively.

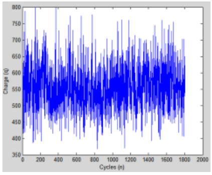

Fig.11 (a) Mean plot (n-q) of data2

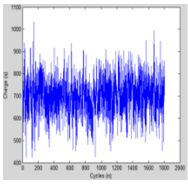

Fig.11 (b) Standard deviation plot (n-q) of data2

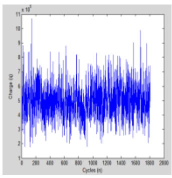

Fig.11 (c) Variance plot (n-q) of data2

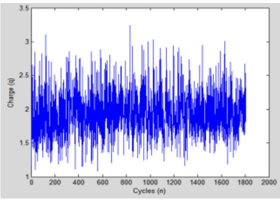

Fig.11 (d) Skewness plot (n-q) of data2

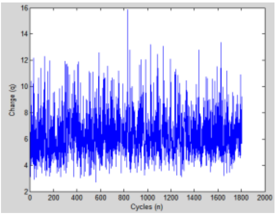

Fig.11 (e) Kurtosis plot (n-q) of data2

In Fig. 11(a), Fig. 11(b), Fig. 11(c), Fig. 11(d) and Fig. 11(e), the charges are uniformly distributed similar to surface discharge. Hence, it can be concluded that data2 is having surface discharge.

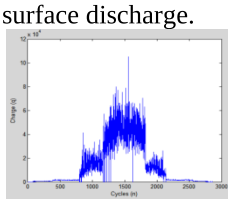

Fig.12 (a) Mean plot (n-q) of data3

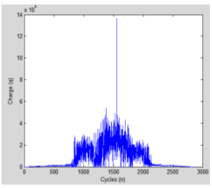

Fig.12 (b) Standard deviation plot (n-q) of data3

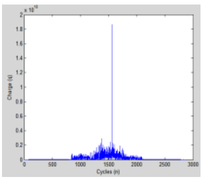

Fig.12 (c) Variance plot (n-q) of data3

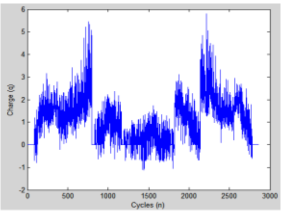

Fig.12 (d) Skewness plot (n-q) of data3

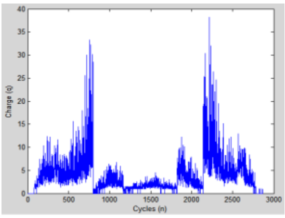

Fig.12(e).Kurtosis plot (n-q) of data3

Fig. 12(a), Fig. 12(b), Fig. 12(c), Fig. 12(d) and Fig. 12(e) are the n-q plot of mean, standard deviation, variance, skewness and kurtosis for data3 respectively. In Fig. 12(a), Fig. 12(b) and Fig. 12(c), there is a occurrence of peak after 1500 cycle and in Fig. 12(d) and Fig. 12(e), the skewness and kurtosis value decreases at that peak which is similar to void discharge. Hence, it can be concluded that data3 is void discharge.

3.3.4. Parameters of unknown PD patterns

TABLE VI. PARAMETERS OF UNKNOWN PD PATTERNS

Parameters	data1	data2	data3
Mean	105.119	553.93	13320.32
Standard deviation	97.966	698.3	7553.716
Variance	16714.23	$4.94*10^5$	$1.64*10^8$
Skewness	0.692	1.939	$-3.7*10^{-17}$
Kurtosis	2.004	6.31	0.04878

4. OBSERVATIONS FROM STATISTICAL METHODS

From the above results, following observations are made:

- Fig. 13(a), Fig. 13(b) and Fig. 13(c) are the characteristics of skewness and kurtosis ($H_{qn}^{+}(\varphi)$ and $H_{qn}^{-}(\varphi)$) of data 1, data2 and data3 against void., surface and corona discharges respectively.
- From Fig. 13(a), it is observed that data3 characteristics overlaps void discharge characteristics, it can be concluded that data3 is void discharge. Data2 characteristics approximately fits against void, it can be concluded that data2 is also void discharge
- From Fig. 13(b), it is observed that data 1 characteristics is similar to surface discharge characteristics, it can be concluded that data 1 is surface discharge.
- From Fig. 13(c), it is observed that none of the data characteristics is similar to corona discharge characteristics, it can be concluded that none of the data has corona discharge.

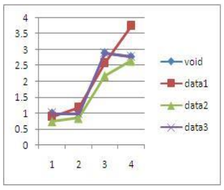

Fig.13 (a) Characteristics of skewness and kurtosis($H_{qn}^{+}(\varphi)$ and $H_{qn}^{-}(\varphi)$) of data1, data2, and data3 against void

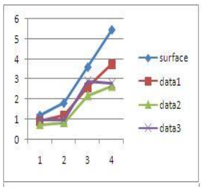

Fig.13 (b) Characteristics of skewness and kurtosis($H_{qn}^{+}(\varphi)$ and $H_{qn}^{-}(\varphi)$) of data1, data2, and data3 against surface

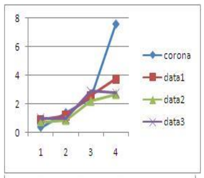

Fig.13 (c) Characteristics of skewness and kurtosis($H_{qn}^{+}(\varphi)$ and $H_{qn}^{-}(\varphi)$) of data1, data2, and data3 against corona

Fig. 14(a), Fig. 14(b) and Fig. 14(c) are the characteristics of skewness and kurtosis ($H_{n}^{+}(\varphi)$ and $H_{n}^{-}(\varphi)$) of data 1, data2 and data3 against void., surface and corona discharges respectively.

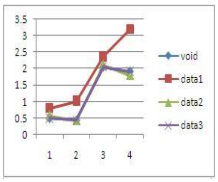

Fig.14 (a) Characteristics of skewness and kurtosis($H_{n}^{+}(\varphi)$ and $H_{n}^{-}(\varphi)$) of data1, data2, and data3 against void

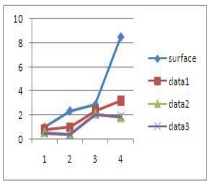

Fig.14 (b) Characteristics of skewness and kurtosis($H_{n}^{+}(\varphi)$ and $H_{n}^{-}(\varphi)$) of data1, data2, and data3 against surface

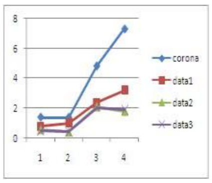

Fig.14 (c) Characteristics of skewness and kurtosis($H_{n}^{+}(\varphi)$ and $H_{n}^{-}(\varphi)$) of data1, data2, and data3 against corona

From Fig. 14(a), it is observed that data3 characteristics overlaps void discharge characteristics, it can be concluded that data3 is void discharge. Data2 characteristics approximately fits against void, it can be concluded that data2 is also void discharge. From Fig. 14(b), it is observed that data 1 characteristics is close to surface discharge characteristics, it can be concluded that data 1 is surface discharge. From Fig. 14(c), it is observed that none of the

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data characteristics is similar to corona discharge characteristics, it can be concluded that none of the data has corona discharge.

Fig. 15(a) is the statistical characteristics of mean, standard deviation, variance, skewness and kurtosis of void discharge against data3. Fig. 15(b), Fig. 15(c) are the statistical characteristics of mean, standard deviation, variance, skewness and kurtosis of surface discharge against data1 and data2 respectively.

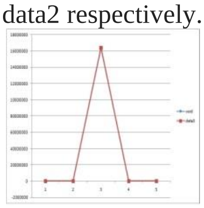

Fig.15 (a) Statistical Characteristics of data3 against void discharge

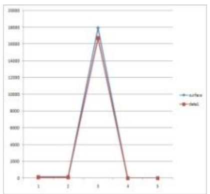

Fig.15 (b) Statistical characteristics of data1 against surface discharge

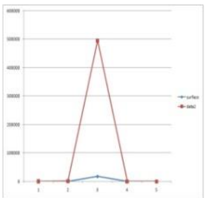

Fig.15 (c) Statistical characteristics of data2 against surface discharge

Plotting statistical parameters of void discharge against data3 in Fig. 15(a) shows data3 characteristics overlaps void characteristics, it can be concluded that data3 is void discharge. Similarly, for surface discharge, data1 and data2 characteristics (Fig. 15(b) and Fig. 15(c)) approximately fit surface discharge characteristics, it can be concluded that data1 and data2 is surface discharge

5. DISCUSSION ON RESULTS OF STATISTICAL PARAMETERS

From all the above observations using all the three phase-resolved patterns (φ-q), (φ-n) and (n-q), it can be concluded that, data1 is surface discharge in all the three phase-resolved patterns, data2 is surface discharge in (n-q) pattern and void discharge in (φ-q) and (φ-n), hence data2 is both void and surface discharge and data3 is void discharge in all the three phase-resolved patterns.
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.
However it is felt that in data2, the type of discharge is slightly vague and in data1, data3 the type can be further ascertained by using latest techniques of Neural Networks. Hence, method of BPM of ANN was tried.

6. BACK PROPAGATION METHOD OF ARTIFICIAL NEURAL NETWORK

This Neural Network is named as Back Propagation method owing to its method of dealing with the error.. It comprises of an input layer, at least one hidden layer and the output layer. Each layer is completely connected to the succeeding layer. The number of processing elements (neurons) in the input layer is equal to the number of feature parameters selected for classification. The number of neurons in the output layer is equal to the number of PD types classification [13].

6.1. Importing Data

Firstly, pre-processing of data is carried out using Statistical parameters like mean, standard deviation, variance, skewness and kurtosis and a rough result is made about PD type. For accurate detection of partial discharge type, nntool built in Matlab is used which gives better results in the following GUI (Graphical User Interface) or nntool window.

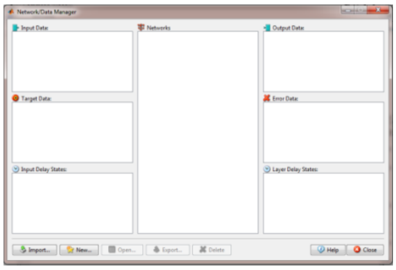

Fig. 16. Network/Data Manager Window

Input data statistical parameters are imported in column INPUT DATA and targets which are decided by the user are imported in column TARGET DATA as follows:

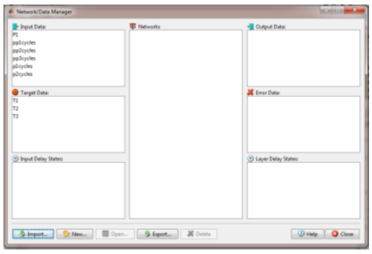

Fig. 17. Input data and Target data Imported in Network/Data Manager

Where,

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

6.2. Creating a New Network

Larger networks require large training datasets. Over fitting is more likely when the model is large.

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Then, a network is created using NEW command in nntool feature of Matlab. Following window appears where network properties are set.

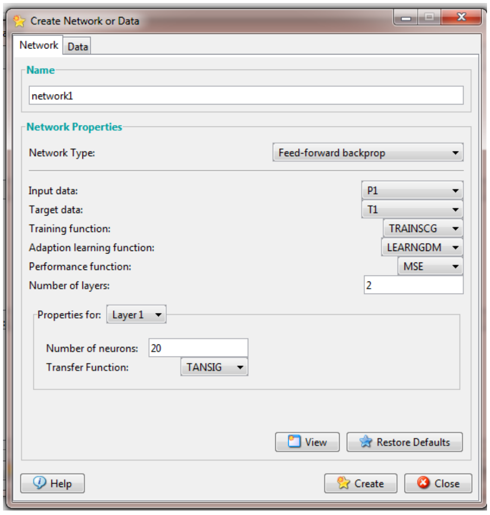

Fig. 18. Creating Network or Data Window

Where,

- Network type: Feed-forward back propagation
- Input data: P1
- Target data: T1
- Training function: TRAINSCG
- Adaption learning function: LEARNGDM
- Performance function: MSE
- Number of layers: 2
- Properties for Layer1 are:
- Number of neurons: 20
- Transfer function: TANSIG

Then, using Create, NETWORK 1 is created.

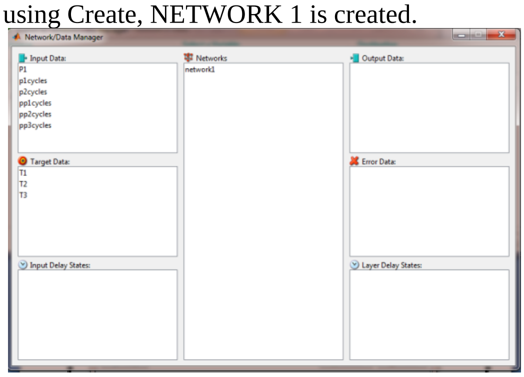

Fig. 19. Network created window

Then, by clicking on network1, following window appears:

6.3. 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. Then, the training, or learning, begins.

There are two approaches to training - supervised and unsupervised.

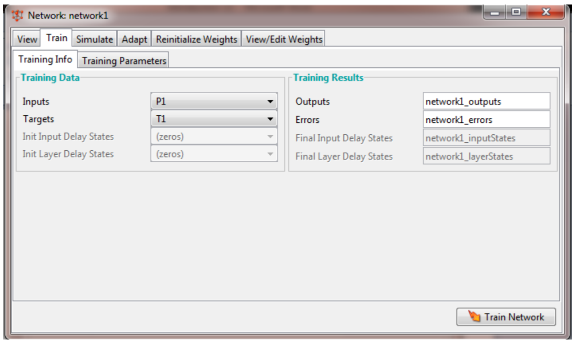

Fig. 20. Training Window

In train menu bar of network1, inputs and targets are fed in training data.

- Inputs: P1
- Targets: T1

Network1 is trained by clicking on Train Network. Neural Network Training (nntraintool) appears which displays the training of the network.

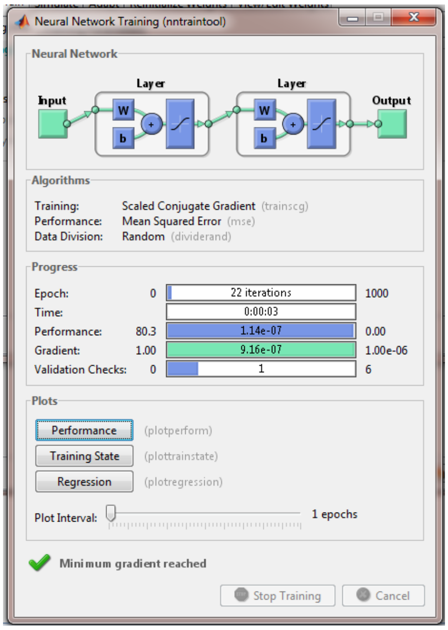

Fig. 21. Neural Network Training (nntraintool) Window

6.4. Simulation

After the neural network classifier has been trained, the next step is to determine whether the resulting model of neural network is with the set of best weights and accurate enough for putting 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.

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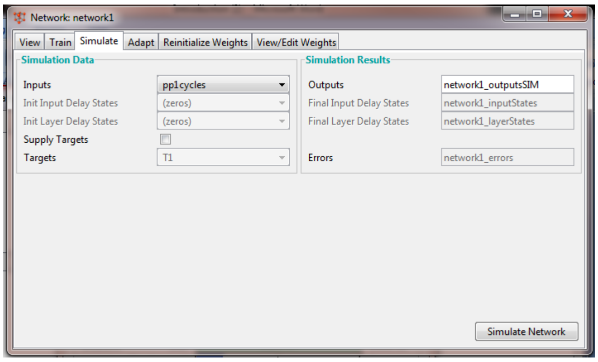

Fig. 22. Simulating Window

In Simulate menubar, inputs are fed in simulation data and output is obtained in simulation results.

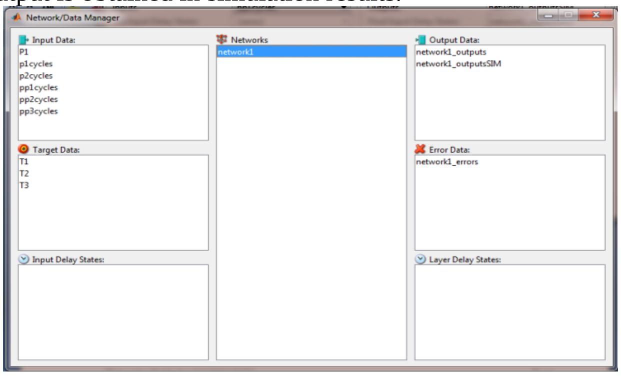

Fig. 23. Simulated Output Window

6.5. Output

Classification of PD using neural networks is an important, fascinating and complex topic. The random initialization of network weights prior to each execution of the neural network training algorithm may cause final classification results to vary from execution to execution in some cases, 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 better 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 neural network classifications.

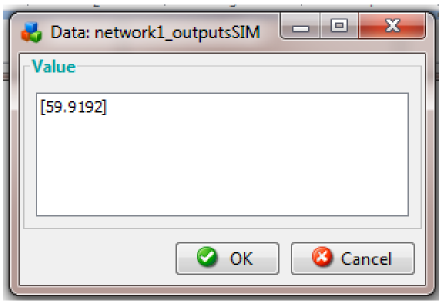

Fig.24. Output Window

The simulated output obtained 59.9192, which is approximately close to the target of surface discharge because we have given target as T1 for training so in that 50 target is decided for void, 60 for surface and 70 for corona. If we are selecting T2 then 60 is for void, 70 for surface and 50 is corona and so on. Hence, it can be concluded that data1 is surface discharge. Similarly, the simulated results are obtained for other unknown PD data.

TABLE VII: Outputs

Sr. No.	Unknown data	Partial discharge Source
1	Data 1	Surface
2	Data 2	Void/surface
3	Data 3	Void

7. CONCLUSION

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.

The ANN on execution produce the same results as obtained in Statistical Method for data1 and data3 resulting in accuracy of the results but again produce dual results for data2 indicating the need for more input samples in training data set so need to use other advanced software Python and other methods of Artificial Neural Network such as Random Forest method, Self organizing map and Support Vector Machine so as to further increase the accuracy in detecting type of PD. From the present work, we can make observe that PD type can be classified using the phase resolved pattern and can be given as the input. It is also possible to detect multiple sources of breakdown those exist in insulation along with determining exact percentage of that type using self organizing map method of ANN in software Python. In future work we aim at developing ANN trained using methods other than back propagation.

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