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# Partial Discharge defects recognition using different Neural Network Model at XLPE cable under DC stress

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***Abstract-***There are many advantages and applications of DC-XLPE cables under DC stress, it is of paramount importance that it is required to have some reliable diagnosis system to check the insulation state of cable insulation in order to avoid the unpredictable service failures of the cable system. Thus, it has been conceived that partial discharge diagnosis is one of the major tools for this purpose. However, very few research works have been reported regarding the PD diagnosis on XLPE cable under the DC stress.

By keeping this fact in mind in the current work, PD detection has been carried out using artificial defects introducible into DC-XLPE cable system and then PD signals have been analyzed by use of Chaotic Analysis of Partial discharge (CAPD). Afterwards, the application of the artificial neural network has been done in order to improve the recognition rate of the PD defects by adding power spectrum data for the first time in this concerned area. In this method, the power spectrum data of the PD signal is combined with CAPD data as the training data for artificial neural networks models. And then different NN techniques have been applied for the recognition of PD defects by using CAPD data and CAPD data combined with power spectrum data. As a result, better recognition rate as well as low mean square loss by using CAPD data combined with Power spectral data, also the MLP techniques has shown best results among all other NN networks.

***Keywords-***Partial Discharge PD, Chaotic Analysis of Partial Discharge CAPD, Neural Network (NN), XLPE Cable.

## I. INTRODUCTION

Most of the service failure in power apparatus is due to the occurrence of Partial discharges from the presence of various natures of defects or irregularities existing at any place in the insulation system. A Partial Discharge (PD) is alocal electrical discharge caused by the excessive local electric filed beyond the breakdown strength of the insulation. And gradually bridging the insulation gap of the insulation system is taken place due to the unexpected propagation of the electrical trees. Fig. 1 below describes schematically that how the PD is occurred in small cavities present in the insulation structure for the power apparatus. Techniques have been proposed for the identification of PD in AC electrical apparatus in ceramic and polymeric insulators [i-v]. For the PD in AC-XLPE cables, several methods have been proposed for the related diagnosis by applying different sensors in the cable insulation as well as cable joints [vi-xi].

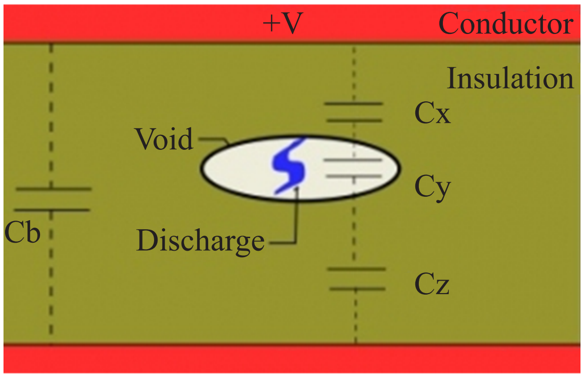


Fig. 1. The small cavity inside the insulating material responsible for PD

In case of power cable insulation system, the process from PD occurrence to breakdown is shown in Fig. 2.

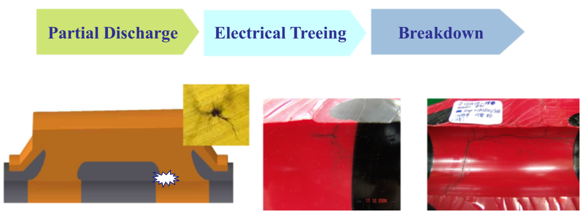


Fig. 2. The breakdown process of insulation due to Partial discharge.

Recently the DC apparatus had been developed with the expectation of less transmission losses. So far, not many techniques have been proposed for diagnosing the reliability of insulation in DC power apparatus instead of its huge applications to the large power grids [xii-xiii]. The Ultra-High Frequency (UHF) Sensors are used to detect the PD under DC stress [xiv]. The diagnosis and evaluation of high power DC apparatus are used to detect PD which is accepted as a plausible diagnostic method for the status of insulation state [xv-xx]. The PD signals are generated from different insulation defects connected to the XLPE cable put under DC stress by using CAPD method and the defects patterns are proposed [xxi].

The Fuzzy Identification System has been proposed in order to identify corona, internal and surface discharge: easy for the corona but hard to distinguish the internal and surface discharges. For that, the characteristics of internal and surface discharge have been expressed as a function of temperature and humidity as well. However, it requires additional facilities such as oven and humidity chamber to investigate the effects of temperature and humidity.

A statistical correlation between consecutive PD events is been proposed to identify PD sources under the DC stress, which is unable to show any specific pattern for the type of defects detected. Moreover investigation parameters of Weibull distribution could not distinguish the PD and noise nor differentiate the type of PD defects.

These parameters obtained from each PD signal are mapped onto two dimensional Time- Frequency plane and then mapped points are clustered respectively in different manner making a region on this plane. In this way, the clustered zone could be separated into "Noise" group from the noses at the site and "PD" group for the PD signals from the defects. The signals in the "PD group" are used for further analysis enabling to make pattern recognition of the defects. [xxii].

From the review on the precedent works, it has been remarked that the main problem to diagnose PD patterns under DC stress is to distinguish the patterns from the different type of defects. For this purpose, it is necessary to develop a more reliable and accurate PD pattern recognition tool and accordingly CAPD method has been selected.

The Pulse Sequential Analysis (PSA) is basically related to the accumulation of local space charges due to change in the local electric field. In PSA there is a strong correlation between consecutive discharge pulses. This means that successive PD pulses cannot be considered to be independent without a correlation with preceding discharge pulses. Because of this in PSA the important parameters like applied voltage or the phase angle do not have the absolute value where the discharges occurs. This is because the local electric field and its effect has to be considered when finding out the values of these parameters.Due to these discrepancies this technique is not used for the current work.

In CAPD Method the absolute value of the magnitude of the PD pulses and time interval between two consecutive PD pulses are the two main parameters taken into the account

## II. Experimental Test Setup and Partial Discharge Detection

The complete experimental test setup is shown in Fig. 3. It consists of a PD free 100 kV transformer which produce AC signal, AC to DC rectifier circuit, Voltage divider to measure DC voltage, XLPE cable specimen, PD defect to produce PD signal, HFCT sensor to receive PD signals and Lab VIEW system as a data acquisition module.

The voltage source is PD free (HAEFLEY 100 kV, 1A) transformer, located inside the well shielded room as shown in Fig. 4, connected with the XLPE cable specimen including a joint. A converting system from AC to DC (150 kV/50 mA) through rectifier (1.5% ripple without load) is shown in Fig. 5.

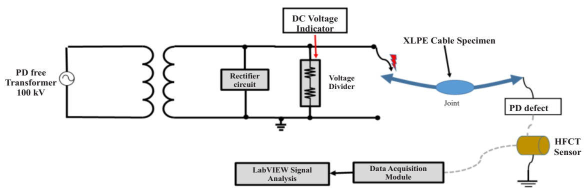


Fig. 3. Experimental Test system diagram


Fig. 4. The XLPE cable with a PD free 100 KV Transformer

Fig. 5. AC to DC rectifier circuit

PDs are detected through a HFCT sensor, clamping the ground wire as in Fig. 6, with the following characteristics: Its bandwidth ranges from hundreds of kHz to 25 MHz, sensitivity is 1 pC ± 1%. The data acquisition module is of National Instruments NI-PXI-5152 with the data rate of 2 GS/sec and having frequency range of 300 MHz as shown in Fig. 7.

Fig. 6. Calvus HFCT Sensor


Fig. 7. National Instruments NI-PXI-5152 System

## A. *Artificial Defects & Partial Discharge*

Three main artificial defects are prepared in order to produce void discharge, surface discharge and corona discharge. Afterwards, they are connected to the sample cable terminal in order to produce PD for the experimental investigation at the laboratory.

*i) Artificial defect for Void discharge*

The presence of void in the cable insulation is imitated by the cavity introduced into the epoxy as shown in Fig. 8in a way to have the same electric field distribution as that of produced in real cable. [xxiii-xxvi] and then it has been put under applied DC voltage at the laboratory. Fig. 8 shows the artificial void defect containing cavity to imitate void and Fig. 9 is its schematic description.

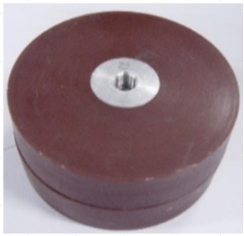

Fig. 8. Artificial Void defect

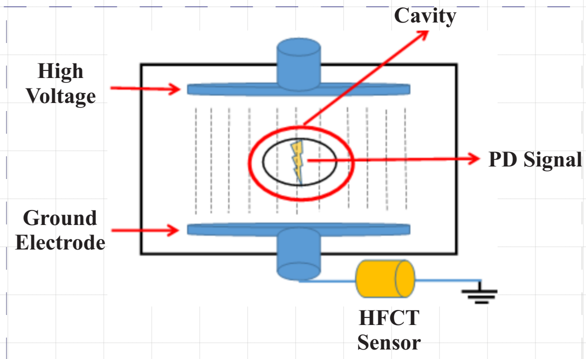


Fig. 9. Cavity imitating Void

*ii) Artificial Defect for Surface discharge*

The Surface discharge occur along the dielectric interfaces where ionization propagates orthogonal to the applied electric field. In order to simulate the discharge at the surface, a solid insulation polymer disk is placed between high voltage and ground terminal as shown in Fig. 10 [xxvii, xxviii].

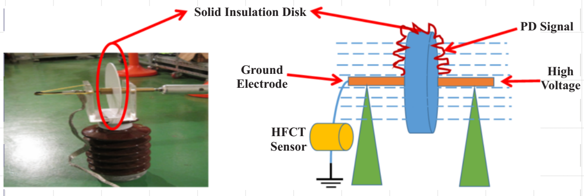


Fig. 10. Circular insulation disk for Surface Discharge showing tangential electric field

*iii) Corona discharge defect*

Corona discharge are produced as a result of high divergent electric field spots which are produced by use of a sharp steel wire intentioanlly located at the ned of sample cable terminal as shown in Fig. 11.

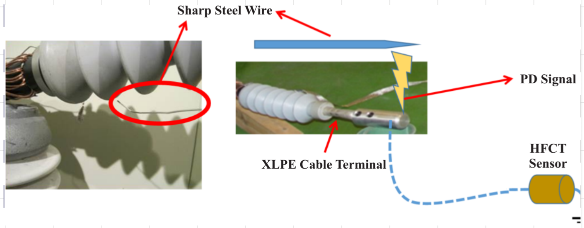


Fig. 11. Sharp steel wire located within the electric field of the terminal to produce Corona discharge

# III. NEURAL NETWORKS

## A. *Process*

After getting the input feature vector of the size 1 × 3072 obtained by three CAPD pattern data, thepattern recognition is carried out by adopting three different neural network techniques which are the Multilayer perceptron (MLP), Self-Organizing Feature Mapping (SOFM) and Recurrent Network (RN). Fig. 12 shows the overall process for the pattern recognition of the defects [xxviii-xxxix].

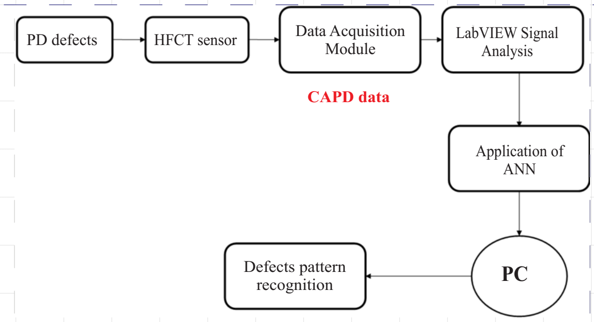


Fig. 12. Flow Diagram of pattern recognition process

### B. *Pattern Recognition Using Multilayer Perceptron (MLP) Neural Networks*

The structure of MLP is shown in Fig. 13. The MLP system been has trained using three hidden layers and each layer has 50, 20 and 10 hidden nodes respectively to converges the system smoothly and quickly.

Fig. 13 shows the total number of input vectors i.e. 3072 along with the hidden layers and the output layer of MLP by showing the three type of outputs as well.

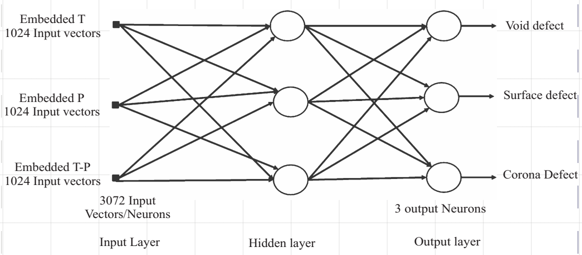


Fig. 13. Input and Output vectors for MLP Neural Networks

### C. *Pattern Recognition Using Self-Organizing Feature Map (SOFM) Neural Networks*

It is a two-layer network that consists of an input layer in a line and an output layer made of neurons in a two dimensional grid as shown in Fig. 14. It uses the unsupervised learning in which the network has to train itself through its own classification without any external source.

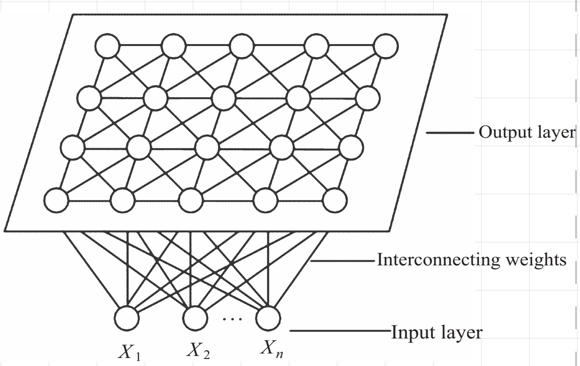


Fig. 14. The architecture of SOFM Neural Network

### D. *Pattern Recognition Using Recurrent Network (Elman Network)*

The main characteristics of a Recurrent Neural Network (RNN) is that it contains at least one feed-back connection from output layer to the hidden layer, so that the activations can flow round in a loop. The learning scheme is the same as for the MLP network using gradient descent procedures similar to the back-propagation algorithm used in feed-forward networks. Every layer is connected to the previous layer making a temporary memory space. This network may use their internal memory to process their arbitrary sequences. There is feedback loop around each layer except the last layer. Fig. 15 shows the architecture of RNN showing the input layer, hidden layer and the output layer along with the feedback loop from the output to the hidden layer.

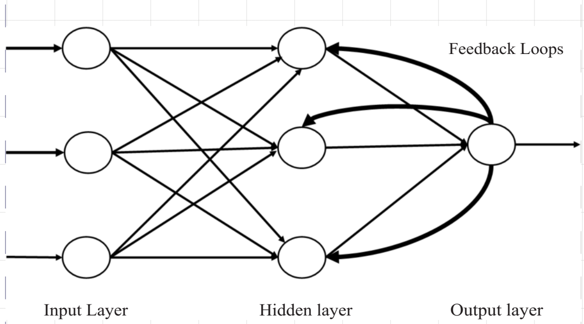


Fig. 15. The architecture of Recurrent Neural Network

### E. *Power spectrum data added with CAPD data*

To get the feature vector from the power spectrum data, the value of PD signals in dBm is acquired from the data of spectrum analyzer using Lab VIEW software as shown in Fig. 16. The power value measured for each PD signal is shown in Fig. 17, which is normalized within the range of 0 to 1 by applying the formula as shown in Eq. 4. Afterwards, a feature vector is also made from these values of the size 1 ×1024 as shown in Fig. 18.

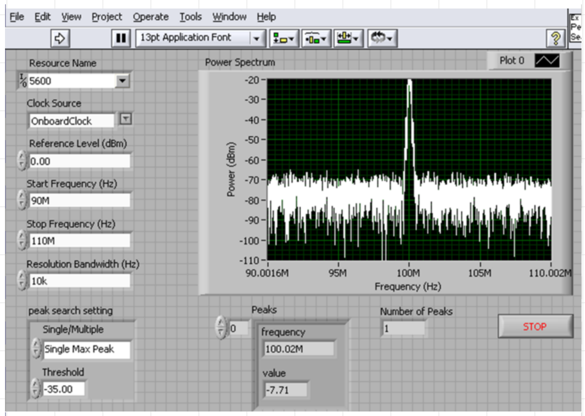


Fig. 16. Waveform of the Spectrum Analyzer in Lab VIEW

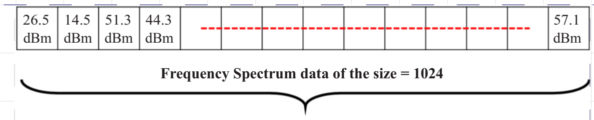


Fig. 17. Power values of Frequency Spectrum [dBm]

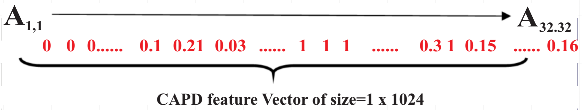


Fig. 18. Power Spectrum feature vector

$$p_f^* = \frac{p_f}{p_{f\max}} (0 \le p_f^* \le 1) \quad (1)$$

Where

- $p_f^*$ = Normalised power of each PD signal
- $p_f$ = Power of each PD signal [dBm]
- $p_{f\max}$ = Maximum power of any PD signal [dBm]

The spectral analysis is dependent on the nature of defects but by using this data alone, it is insufficient to recognize the defects producing any PD signals, however, if it is added with other PD signal data, a better recognition rate could be obtained. Thus, spectral feature vector is considered to be added with the feature vectors of CAPD data. The input vector obtained by combining these feature vectors is fed into the neural network to enhance the pattern recognition rate. For this purpose, the input vector is composed by adding the CAPD feature vector of the size 1 × 3072 and one feature vector of power spectrum data of the size 1 × 1024 by making input vector of the size 1 × 4096 which is used as a training data for NN as shown in Fig. 19. The block diagram showing the overall process of pattern recognition is shown in Fig. 20.

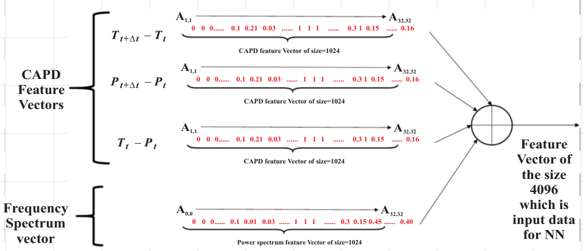


Fig. 19. Input feature vector of the size 1 × 4096

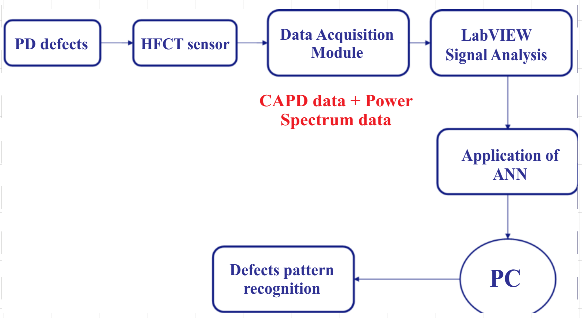


Fig. 20. Block Diagram of Pattern recognition process

The pattern recognition process is performed by adopting three different neural network techniques including Multilayer perceptron (MLP), Self-Organizing Feature Mapping (SOFM) and Recurrent Network (RN).

Fig. 21 shows the total number of input vectors i.e. 1 × 4096 along with the hidden layers and the output layer by showing the three outputs.

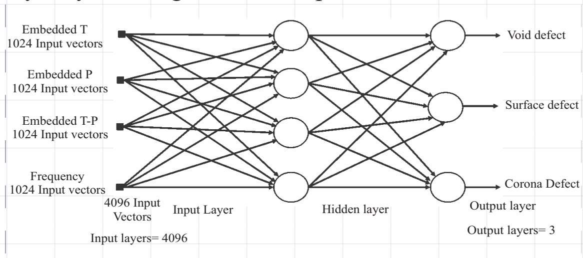


Fig. 21. Input and output vectors for Neural Networks

### *F. Comparison Of Results Based On CAPD Data With Power Spectral Data*

The numbers training data and testing data for the three neural networks is summarized in Table I.

TABLE I
THE NUMBER OF TRAINING AND TESTING DATA

| Defect Type | Data sets of Multilayer Perceptron (MLP) | | Data sets of Self Organizing feature Map (SOFM) | | Data sets of Recurrent Network (RN) | |
|---|---|---|---|---|---|---|
| | Training data | Testing data | Training data | Testing data | Training data | Testing data |
| Void | 86 | 42 | 112 | 57 | 95 | 47 |
| Surface | 118 | 59 | 107 | 54 | 90 | 42 |
| Corona | 105 | 37 | 102 | 45 | 98 | 45 |

The input vector and objective output vector is shown in Table II. When the learning phase is completed, one of the three output of the defect is equal to '1' and the other two are equal to '0' showing the correct type of the defect.

TABLE II
THE OBJECTIVE OUTPUT VECTOR

| Input Vector | Objective Output vector | | |
|---|---|---|---|
| | Void | Surface | Corona |
| Void | 1 | 0 | 0 |
| Surface | 0 | 1 | 0 |
| Corona | 0 | 0 | 1 |

### *G. Overall Comparison Of Recognition Rates*

The overall comparison of MSEs of the defects using different NN techniques are compared for two cases obtained by only CAPD data and CAPD data combined with power spectrum data are shown in Table. II. The latter one is found to be lower as compared to that from the former one. And MLP technique has shown the results with least MSEs as compared to other two techniques when the CAPD data is combined with power spectrum data.

TABLE. III
MEAN SQUARE ERROR (MSE) DEPENDING USING ONLY CAPD DATA AND CAPD DATA WITH POWER SPECTRAL DATA

| Neural Model | Mean Square Error (MSE) | | | |
|---|---|---|---|---|
| | CAPD Data + Spectral Data | | Only CAPD data | |
| | Training | Testing | Training | Testing |
| Multilayer Perceptron (MLP) | **0.006** | **0.012** | 0.034 | 0.043 |
| Self-Organizing Feature Map (SOFM) | 0.015 | 0.017 | 0.173 | 0.161 |
| Recurrent Network (RN) | 0.009 | 0.035 | 0.057 | 0.089 |

The overall comparison of recognition rates using different NN techniques are also compared for two cases obtained by only CAPD data and CAPD data combined with frequency spectrum data in Table IV. pattern recognition rate of the former is less as compared to that of the latter. Also as a whole, the MLP technique has shown the best performance.

TABLE IV
PATTERNS RECOGNITION RATES BY CONSIDERING ONLY CAPD DATA AND CAPD DATA WITH SPECTRAL DATA FOR THREE ANN TECHNIQUES (UNIT: %)

| Type of Defects | Recognition Rate (%) | | | | | |
|---|---|---|---|---|---|---|
| | Multilayer Perceptron (MLP) | | Self-Organizing feature Map (SOFM) | | Recurrent Network (RN) | |
| | CAPD data + Spectral Data | Only CAPD Data | CAPD data + Spectral Data | Only CAPD Data | CAPD data + Spectral Data | Only CAPD Data |
| Void | 97.31 | 76.14 | 87.41 | 77.34 | 95.14 | 89.65 |
| Surface | 95.85 | 80.45 | 83.57 | 69.12 | 90.34 | 84.23 |
| Corona | 99 | 83.34 | 84.79 | 68.76 | 91.25 | 73.56 |
| Average | 97.38 | 78.60 | 85.25 | 71.47 | 92.24 | 82.48 |

## IV. RESULTS AND DISCUSSIONS

It could be concluded from these analyses that, in order to improve the recognition rate of PD defects, it is effective to combine the CAPD data with frequency spectrum data of PD signals: MLP technique has shown the best recognition rates and least MSEs.

## V. CONCLUSION

The Partial Discharge (PD) under DC stress has been produced by use of artificial defects imitating vital insulation defects introducible into the cable system such as void, surface and corona. It has been generally conceived that their presence could give rise to a considerable service failure of the DC XLPE power cable system. By keeping this fact in mind, this work has been proposed to carry out an experimental investigation followed by the pattern recognition of the above defects by using CAPD method. For the latter, one more parameter, such as frequency spectrum data of the PD signal, has been additionally considered together with the CAPD data. Finally, the pattern recognition rate obtained by only CAPD data and CAPD data combined with spectral data has been compared, for which different NN techniques have been applied respectively.

In order to acquire the PD parameters using CAPD method, the magnitude of the PD pulses and the time interval between two consecutive pulses have been used to represent the related PD patterns. Three different type of patterns have been obtained from each defect of which the feature vectors are extracted from CAPD data patterns to obtain the pattern recognition rates. In order to get the feature vector, the 2-dimensional CAPD data patterns have been transformed into one dimensional feature-vector. Three feature vectors have been obtained for each type of defects and then are used for training data. Afterwards, different neural networks techniques have been applied for comparing the results: Multilayer perceptron (MLP), Self-Organizing Feature Map (SOFM) and Recurrent Network (RN).

In order to improve the recognition rate of PD defects, the frequency spectrum data is also added with CAPD data. The training is again performed by using three feature vector obtained from each CAPD defect data along with one feature vector obtained from frequency spectrum data by using different NN techniques like above.

Finally, the recognition rates of PD defects iscompared for both the data. It is shown that the data combining CAPD and spectrum data shows much better performance as compared to the previous case in term of low mean square error and better recognition rates. Also, the MLP technique has shown the best results among the three techniques.

In future, this idea can be applied to recognize different PD defects and as a result better recognition rate can be achieved which results in avoiding the power apparatus failures and to avoid heavy damages.

## REFERENCES

[i] A. Cavallini, G.C. Montanari, F.Puletti., A. Contin 'A New Methodology for the Identification of PD in Electrical Apparatus: Properties and Applications', IEEE Trans. Dielectr. Electr. Insul, 2005, Vol. 12, pp. 203-215.

[ii] A. Cavallini, G. C. Montanari and F. Puletti., 'A

Novel Method to locate PD in Polymeric Cable systems based on the Amplitude –frequency (AF) Map', IEEE Trans. Dielectr. Electr. Insul, 2007, Vol. 14, pp.726-734.

[iii] S. Chandrasekar, C. Kalavanan, G.C. Montanari, A. Cavallini, 'Partial Discharge detection as a Tool to Infer Pollution Severity of Polymeric Insulators', IEEE Trans. Dielectr. Electr. Insul, 2010, Vo. 12, pp. 181-188.

[iv] A. Cavallini, S. Chandrasekar, and G. C. Montanari., F. Puletti, 'Inferring Ceramic Insulator Pollution by an Innovative Approach Restoring to PD Detection', IEEE Trans. Dielectr. Electr. Insul, 2007, Vol. 14, pp. 23-29.

[v] S. Chandrasekar, C. Kalaivanan, A. Cavallini., G. C.Montanari 'Investigation on Leakage Current and Phase Angle Characteristics of Porcelain and Polymeric Insulator under contaminated Conditions', IEEE Trans. Dielectr. Electr. Insul, 2009, Vol. 16, pp. 574-583.

[vi] Y. J. Lee, J. Y Kim, I. J. Seo., 'Frequency characteristics of Partial discharge in MV extruded cable using non-conventional Sensors', 8th International Conference on Insulated Power Cables, Versailles, France 2008.

[vii] W. Choi, I. J. Seo, Y. J. Lee, 'An Algorithm development for finding PD sources located in 154kV XLPE power cable system', International conference on Conditioning Monitoring and Diagnosis (CMD), Jeju, Korea, 2014.

[viii] J. Y. Koo, J. S. lee and J. T. Kim., 'A Study on the correlation between the PD pattern and the aspect of electrical trees propagation in the XLPE insulation of the underground power transmission cable', The 6th International Conference on Properties and Applications of Dielectric Materials, China, 2000.

[ix] J. T. Kim, D. U. Kim, Y. J. Lee, 'Analysis of Partial Discharge Inception Voltages for wrong positioning defects in the Joint of Distribution Power Cables', J Electr Eng Technol, 2013, Vol. 7, pp. 977-982.

[x] J. S. Lee, J. Y. Koo, Y. S. Lim., J. T. Kim, S. K. Lee: 'An analysis of the Partial Discharge pattern related to the artificial defects introduced at the interface in XLPE Cable joint using laboratory model', Conference on Electrical Insulation and Dielectric Phenomena, 2002.

[xi] J. T. Kim, D. U. Kim, G. J. Nam., 'Partial Discharge location using two sensors and Optical Fiber', IEEE International Conference on Condition Monitoring and Diagnosis, Indonesia, pp. 126-129, 2012.

[xii] Soo-Bong Lee, Tae-Ho Lee, Eui-Hwan Jung.,'Development status of HVDC XLPE cable in Korea', International Conference on Condition Monitoring and Diagnosis (CMD), Jeju, Korea, 2014.

[xiii] T. H. Lee, J. W. Choi, E. H. Jung, 'Development of the HVDC 80kV XLPE cable System and Construction of Test-bed in KOREA', CIGRE 2012.

[xiv] R. Sarathi, A. V. Giridhar, A. Mani., K. Sethupati 'Investigation of Partial Discharge Activity of Conducting Particles in Liquid Nitrogen under DC Voltages using UHF Technique', IEEE Trans. Dielectr. Electr. Insul, 2008, Vol. 15, pp. 655-662.

[xv] S. Wenrong, L. Junhao, Y. Peng, L. Yanming 'Digital Detection, Grouping and Classification of Partial Discharge Signals at DC Voltage', IEEE Trans. Dielectr. Electr. Insul, 2008, Vol. 15, pp. 1663-1674.

[xvi] P. H. F. Morshuis and J. J. Smit, 'Partial Discharge at DC Voltage: Their Mechanism, Detection and Analysis', IEEE Trans. Dielectr. Electr. Insul, 2005, Vol. 12, pp. 328-340.

[xvii] A. Cavallini, G. C. Montanari, M. Tozzi, X. Chen, 'Diagnostic of HVDC Systems Using Partial Discharge', IEEE Trans. Dielectr. Electr. Insul, 2011, Vol. 18, pp. 275-284.

[xviii] H. Q. Nui, A. Cavallini, G. C.Montanari, 'Identification of Partial Discharge Phenomena in HVDC Apparatus" IEEE Conference, 2008.

[xix] A. Cavallini, X. Chen, H. Niu., G. C. Montanari 'Strategies for PD Source Identification in HVDC System" IEEE Conference 2008.

[xx] F. H .Kreugar, "Industrial High DC Voltage", Delft, The Netherland, Delft Univ. Press, 1995.

[xxi] M. Y. A. Khan, I. J Seo, Y. J. Lee., J. Y. Koo.: 'An Insulation defect in HVDC XLPE Cable based on the analysis of PD Detection', International Symposium on High Voltage Engineering(ISH), Pilsen, Czech Republic, 2015.

[xxii] M. R. Rahimi. R. Javadinezhad, Mehdi Vakilian, "DC Partial discharge Characteristics for Corona, Surface and Void discharges", IEEE 11th International Conference on the properties and Applications of Dielectric Materials, 2015.

[xxiii] J. Y. Koo, J. S. Lee, Y. S. Lee, "Comparison of Diagnostic method for the pattern analysis due to artificial defects introduced at the interface in XLPE cable joint using laboratory Model", IEEE Conference 2012, pp. 1426-1430.

[xxiv] Y. Z., Arief, H. Ahmad and M. Hikita, "Partial Discharge characteristics of XLPE cable joint and interfacial phenomena with artificial defects", 2nd International conference on power and energy, Dec 1-3, Johor Baharu, Malaysia, 2008, pp. 1518-1523.

[xxv] J. S. Lee, J. Y. Koo, Y. S. Lim, S. K. Lee, "An analysis of the Partial Discharge pattern related to the artificial defects introduced at the interface in XLPE cable joint using laboratory Model", Annual Report Conference on

Electrical Insulation and Dielectric Phenomena, 2002, pp. 482-485.

[xxvi] Industrial High DC Voltage by F.H.Kreuger.

[xxvii]M. Florkowska, A. Zydron, "Interaction of conductor with Polymeric Materials (XLPE/EPR) at Partial discharges. IEEE Transction on Dielectric and Electrical Insulation, Vol. 19, No.6, Dec 2012.

[xxviii]Partial Discharge detection in High-Voltage Equipment's, By F. H. Kreuger.

[xxix] L. Satish, B.I. Gururaj 'Partial discharge pattern classification using multilayer neural network', 1993, IEE Proceedings-A, Vol. 140, No. 4, pp. 323-330.

[xxx] M. M. A. Salama, R. Bartknikas, 'Determination of Neural Network Topology for Partial Discharge Pulse Pattern Recognition', IEEE Transaction on Neural Network, 2002, Vol. 13, No. 2, pp. 446-456.

[xxxi] Amira A. Mazroua, M. M. A. Salama and R. Bartnikas., 'PD Pattern Recognition with Neural Network using multilayer Perceptron Technique', IEEE Trans. Dielectr. Electr. Insul, Vol.28 No. 6, pp. 1082-1089.

[xxxii]S. Y. Jung, C. H. Ryu, Y. S. Lim, 'Discrimination of Insulation defects in a Gas Insulated Switch Gear (GIS) by use of a Neutral Network based on a Chaotic Analysis of Partial discharge (CAPD)', Journal of Electrical Engineering & Technology, 2007, Vol. 2, No. 1, pp 118-122.

[xxxiii]L. Satish and Walter S. Zaengl, 'Artificial Neural Network for Recognition of 3-d Partial Discharge Pattern', IEEE Trans. Dielectr. Electr. Insul, 1994, Vol. 1 No. 2, pp. 265-275.

[xxxiv]Christian Cachin, and Hans Jurg Wiesmann, 'PD Recognition with Knowledge-based Preprocessing and Neural Networks', IEEE Trans. Dielectr. Electr. Insul, 1995, Vol. 2 No.4, pp. 578-589.

[xxxv]E. Gulski and A. Krivda, 'Neural Network as a Tool for Recognition of Partial Discharge', IEEE Trans. Dielectr. Electr. Insul, 1993, Vol. 28 No. 6, pp. 984-1001.

[xxxvi]H. Borsi, E. Gockenbach, D. Wenzel, 'Separation of Partial discharge from pulse-shaped noise signals with the help of Neural Network', IEE Proc. Sci. Meas. Technol, 1995, Vol. 142, No.1, pp. 69-74.

[xxxvii]Lefteri H. Tsoukalas, Robert E. Uhrig.: 'Fuzzy and Neural Approaches in Engineering', John Wiley and Sons, pp. 229-254.

[xxxviii]M. Y. A. Khan, J.Y.Koo," Neural Network based diagnosis of Partial discharge defects patterns at XLPE cable under DC stress", Electr Eng, Springer, 99, 119-132, 2017.

[xxxix]Soo-Bong Lee, Tae-Ho Lee, Eui-Hwan Jung., 'Development status of HVDC XLPE cable in Korea', International Conference on Condition Monitoring and Diagnosis (CMD), Jeju, Korea, 2014.