“INVESTIGATION OF PARTIAL DISCHARGE IN POWER CABLES USING ARTIFICIAL NEURAL NETWORK AND PD ANALYZER”

D.F.Jingle Jabha

Research scholar, Anna University,Chennai-600 025, T.N., India

Email.brasen1@rediffmail.com,Mobile.no:9442389908.

K.Selvi

Associate Professor, Thiagarajar College of Engineering, Madurai-625 015, T.N., India.

R.Joselin

Associate Professor, C.S.I.Institute of Technology,Thovalai-629302, T.N., India.

ABSTRACT

Partial discharge analyzer (PDA) has the unique potential for evaluating degradation and possibly failure prediction of XLPE cables as well. The authors have demonstrated its capability towards failure prediction on XLPE cables. In this study, five sets of fifty number of identical XLPE cables were taken up for the investigation. These tests were carried out on both damaged and undamaged conditions. The data acquired during their loading cycles is analyzed using Artificial Neural Network (ANN) which is further developed to predict the failure performance of power cable. Using this approach one could appreciate that impending failure is significant even at 50 to 60 % of maximum expected operating voltage (MEOV) with a reasonable error margin. In fact, till date there is no lucid method spelt out in the open literature for the failure prediction of XLPE Cables. Moreover, this methodology can also be applied to predict in real time the failure of similar XLPE cables made of material systems. Also, in order to verify the results, Gaussian Mixture Models (GMM) is used for data analysis. This work can also be further extended to other equipment like transformers, switch gears and rotating machines.

Index Terms **- Partial Discharge; Power cable; Artificial Neural Network; Prediction; GMM**

1. INTRODUCTION

Partial discharge analysis is widely used for both electrical equipment and materials research monitoring applications because of its unique potential for detection and location of dynamic defects under operating conditions. In the past few years, it has been mostly used for testing the underground power cables [1-4]. For underground cable applications, detection of partial discharge is used for preventive / predictive maintenance under medium and high voltage [5,6]. With the rapid advances taking place in this area, there has been a strong need for an analytical technique which can indicate the degradations that take place during the course of the acceptance load testing of electrical equipment [7]. There are cases reported in the open literature bringing to light the fact that XLPE cables that have successfully undergone acceptance tests did fail surprisingly during their actual use [8, 9]. In this respect, Artificial Neural Network (ANN) technique has assumed a unique role to tackle this difficulty. More than evaluating the integrity of cables, ANN has the potential to predict the failure voltage within certain limits. It is well known that XLPE power cables undergo degradation during acceptance tests due to treeing, thermal stresses, corrosion, manufacturing defects, transient over voltage between layers etc. Such degradations can be indicated through its output waveforms [10-14]. Partial discharges are a major source of insulation failure in high voltage power system which needs to be monitored continuously to avoid the incipient failure in the power system network [15,16]. The PD activity inside the solid insulation highly depends on the entire geometry of the void presence inside the solid insulation model [17]. In addition, PD increases with the increase of applied voltage inside the solid insulation. Performance characteristics of different faulty cables during test have been simulated using back propagation neural network [18,19].

In this study, online monitoring is carried out on high capacity XLPE cables for four identical cases. An attempt is made on the fifth XLPE cable to predict its failure voltage. The test was carried out under damaged and undamaged conditions. Each set of cables consists of ten identical specimens. This innovative methodology illustrates the performance of XLPE cables and its failure rates. In this investigation data is acquired only upto 50% of the theoretical failure voltage and then the cables were loaded upto failure. Finally, the prediction was attempted on the XLPE cables well before its actual failure also a methodology is being developed in this paper to estimate the failure of XLPE cables.

2. CABLE DETAILS

This work is performed on five sets of fifty Nos. of similar XLPE cables. All the cables were ISI marked and its specifications are based on IS: 7098(Pt-I)/1988 standard. The used single core aluminium unarmoured power cables consists of 120 sq.mm size, 2000 mm in length and its insulation thickness is 2 mm. In this work, the variation of the maximum PD magnitude with different applied voltage for five various types of specimens are determined. The obtained PDs consist of PD distribution; frequency content and amplitude are also obtained from PD pulse.

3. EXPERIMENTATION

The entire experiment is done at highly protected well- equipped high voltage laboratory. The experiment is carried out using 5 sets of fifty Nos. of XLPE cables with different damages. The entire test is based on the standard of IEC: 60840. The experiments are used to determine the withstanding capability of the cable using its discharge signals during online monitoring. The general block diagram for capturing partial discharge using PD analyzer test is shown in Figure 1 and the specimen preparations are shown in Figure 2.The specification details of studied cables are as follows:

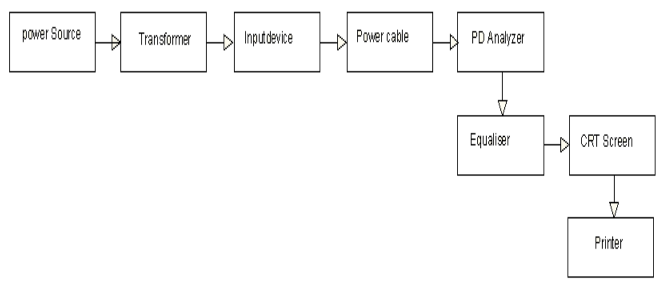


Figure.1 General block diagram for capturing PD using PD analyzer

a.Undamaged cable

b. impact damaged cable

c.2 mm diameter punched cable

d. 1 mm diameter punched cable

e.1 mm thickness hacksaw cut cable

Figure 2. Types of damages in various specimens

3.1 SPECIFICATIONS OF XLPE CABLE

Core type	:	Single Core
Cable type	:	XLPE type HT cable
Conducting Material	:	Aluminium
No. of layers in the conductor	:	19
Type of Insulation	:	PVC Insulation
Overall diameter	:	640 mm
Number of Cables used	:	5 Sets (50 Nos.)
Net Wt. of the cable	:	0.253 Kg/Km
Current carrying capacity	:	205 Ampere
Voltage drop/ampere per meter	:	0.8mV

4. EXPERIMENTAL SETUP

An impulse generator Marx circuit was used to increase the voltage upto 150 kV. The Experimental setup is shown in Fig.3 which consists of Coupling Capacitor, Control Desk, PD Analyzer and PD Monitoring Unit etc. The Impulse generator Marx circuit is used to step up the voltage from 440V to higher. The supply terminal is connected with the conductor of the specimen and ground terminal is connected to insulator which is controlled by the control desk inside the control room. Coupling capacitor setup contains steps of capacitors and some busbar links to connect the various capacitor banks for generating high voltage supply above 11kV. Control desk consists of a variable resistance to vary the output voltage. PD Analyzer is the equipment which records a Partial Discharge pulses from the XLPE cable. The PD Monitoring unit is used to monitoring the discharge signals.It contains digital osciloscope - DSO6032A and a personal computer. The oscilloscope consists of 300MHz bandwidth with two analog channels.

Figure 3. Experimental setup

4.1 EXPERIMENTAL PROCEDURE

Marx circuit is connected with specimen and placed over a wooden stool is illustrated in Fig.4. The control desk is used to turn on the entire system. From the control pannel the voltage is increased gradually from 0 kV to 3kV and recorded the corresponding discharge output signal using the oscilloscope. Similarly, the voltage is increased in 3kV steps upto the occurance of breakdown. The detailed load cycle is as follows:

- Leak Cycle : 0-3 kV (Hold for 5mts)-0 kV.
- I-Load Cycle : 0-3 kV (Hold for 1mt)- 6 kV (Hold for Max. 3mts)-0 kV.
- II- Load Cycle: 0-6 kV (Hold for 1mt)-9 kV (Hold for Max.3mts)-0 kV.
- III- Load Cycle : 0-9 kV (Hold for 1mt)- 12 kV (Hold for Max. 3mts)-0 kV.
- IV- Load Cycle : 0-12 kV (Hold for 1mt)-15 kV (Hold for Max.3mts)-0 kV.
- After the 15-kV cycle, loading was decreased to facilitate removal of all connection and other instrumentation with PD analyzer. Thereafter, the loading will continue at a steady rate till failure.
- The first time hold at various incremental loads shall be for a minimum of 1 mt. During the higher load cycles, in some cases, there will be small amount of spark coming out in the fill end between the holder and the cable. Therefore, during such load cycles, the load ‘hold’ is carefully maintained constant. The maximum hold shall be for a period of 3 mts. At each incremental voltage rise the detector measures PD for one minute. Fig.5 depicts the breakdown of fifth specimen.

Figure 4. Specimen connected with Marx circuit

Figure. 5. Failure of XLPE cables

5. ARTIFICIAL NEURAL NETWORK (ANN)

The emergence of the Artificial Neural Network in the 1990s made the prediction processes faster and more accurate. Moreover, dilation of the cable during loading, local yielding (strain) and peak amplitude are important parameters closely associated with the ultimate burst load were overlooked by researchers. An accurate prediction of failure load is contemplated in this research by involving these parameters with PD analyser data through a neural network. The significance of other parameters like PD distribution, frequency content for failure strength prediction are also planned to be examined. Most of the ANN structures commonly used in many applications, often consider the behaviour of a single neuron as the basic computing unit for describing neural information processing operations. Each computing unit, i.e., the artificial neuron in the neural network is based on the concept of an ideal neuron. A neuron is assumed to respond optimally to the applied inputs. However, experimental studies in neuro-physiology show that the response of a biological neuron appears to be random, and only by averaging many observations it is possible to obtain predictable results. An artificial neural network is an information processing system that has certain characteristics similar to biological neural networks. A neural network consists of a large number of simple processing elements called neurons or nodes. Each of these neurons is connected to other neurons by communication links, each with an associated weighting. The weightings represent information being used by the network to solve a problem. A neuron has many input paths and combines the values of the input paths by a simple summation. The summed input is then modified by a transfer function and passed directly to the output path of the processing element. The output path of the processing element can then be connected to the input paths of other nodes through connection weightings. Since each connection has a corresponding weighting, the signals on the input line to a processing element are modified by these weightings prior to being summed. The processing elements are usually organized into groups called layers. Typically, a network consists of an input layer where data are presented to the network, and an output layer which holds the response of the network, and one or more hidden layers for processing. Fig.6 show the Architecture of fine tuned neural network at high amplitude frequencies.

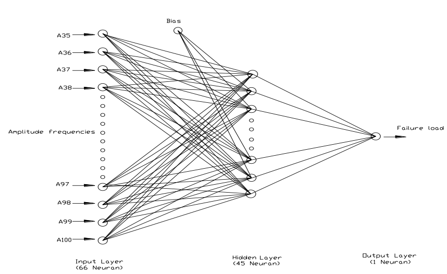
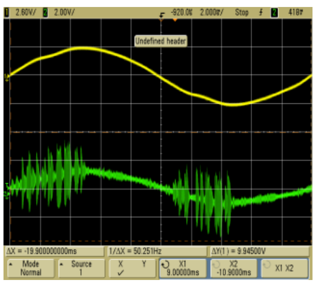


Fig 6. Architecture of fine tuned network at high amplitude frequencies

50 numbers of cable specimens and the corresponding failure load were grouped into five. Each group consists of ten specimen, so that the training set chosen was to include the best and worst failure loads in the data set. Amplitude recorded from the specimens in group1 up to 50% of its failure loads were used to train the network, and their corresponding failure loads were given as the expected output. Only amplitude data up to 50% of failure load of the remaining specimens in next groups were used for testing the network. The feed forward back propagation network in MATLAB-6.0 workspace consist of 66 neuron in the input layer (Each amplitude frequencies from 35dB to 100dB as one neuron) and one targeted output (Failure load) neuron in the output layer as shown in Architecture [20]. After enough experimentation, the optimal learning coefficient and momentum of the network for this application were found to be 0.01 and 0.9 respectively. Levenberg-Marguart algorithm was employed, because of large number of input neurons were present in the network. There are many combinations in the number of middle (hidden) layers neurons were attempted while training the network. Finally, Tansig and purelin transfer functions were used for the hidden layer and output layer respectively. Network with single middle layer consist of as few as 3 processing elements (neurons) to as much as 50 elements were attempted. The best training results were obtained at 66-34-1 network architecture. Targeted convergence threshold was attained at 1500 epochs. The optimum prediction results of other specimens and its errors are presented in Table 1 & 2. Maximum error tolerance of 13.41% was obtained for hacksaw cut specimen. This technique is most suitable for all type of damaged cables. Moreover this approach is better than GMM in case of undamaged cables. It is also identified that the difference of predictions are reasonably better at a range of 0.4 kV to 0.8 kV.

5. RESULT AND DISCUSSION

The PD alalyzer can generate output pulses for all types of cables which is illustrated in Fig.7 & 8. The results obtained from this investigation describe the concluding remarks of all the cables. In each set, ten identical specimens were tested in similar manner. The optimum result is discussed herein. The results obtained from PD analyzer is clustered using fuzzy logic which is further analysed using Artifical Neural Network (ANN). Since there are five types of test and five kinds of dischare modules, each module is experimented with 60% of data sets for training and 40% of data sets for testing. The trained data is further compared with the target values. The training tool is illustrated in Fig.9. From the results of various damaged cables it is identified that punched cables withstand more when compared with cut cable. The failure voltage is predicted using training and testing of various data’s obtained at different voltage steps upto MEOV. The actual breakdown occurred in the cut cable is much earlier than other specimens which is also predicted using neural network analysis with reasonable error margin say, 13.41%. The final output obtained from ANN is shown in Fig.10 to Fig.13. The same analysis was again repeated using wavelet transformation. In this, using the PD analyzer output waveform four levels of detail coefficients are identified which is illustrated in Fig.14. These coefficients are fed into the Gaussian Mixture Models (GMM) in order to cluster. In which individual data points are generated by choosing one set of multivariate Gaussians and sampling them using the well-defined computational operational. Similar procedure is continued for all the types of data set obtained from various specimens. Fig:15 depicts the simulated PD results obtained from GMM after the training. The output represents the variations in the signal waveforms for various cables which indicate the abnormal partial discharge. The overall performance of both ANN and GMM are illustrated in Table.3 and its comparison is shown in Fig.16. The peak amplitude obtained from the PD analyzer is the superior performance in the failure strength prediction exercise at 50% voltage level.



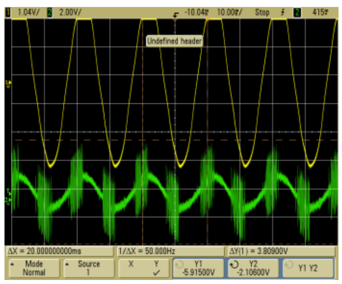


Figure. 7. PD for undamaged cable **Figure. 8.** PD for damaged cable

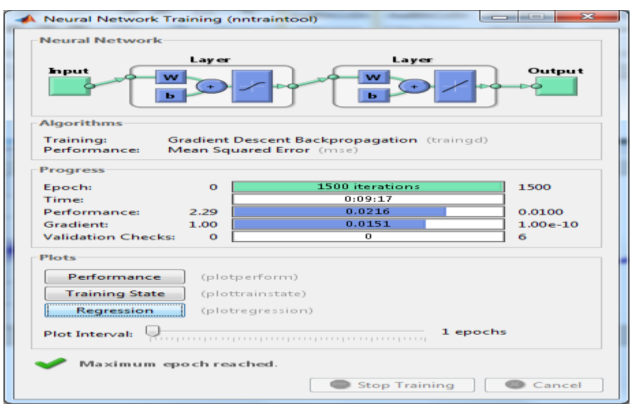
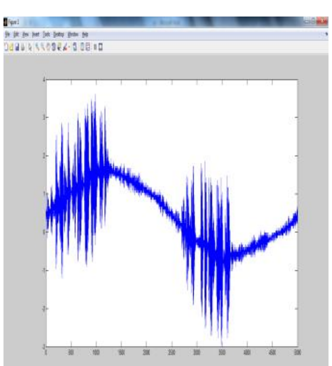


Figure.9 NN Training tool



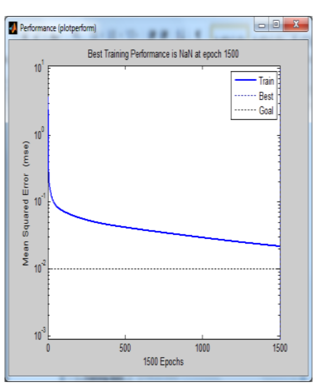


Figure.10 Simulated PD output from ANN **Figure. 11.** Performance of the signal samples with the given data set models.

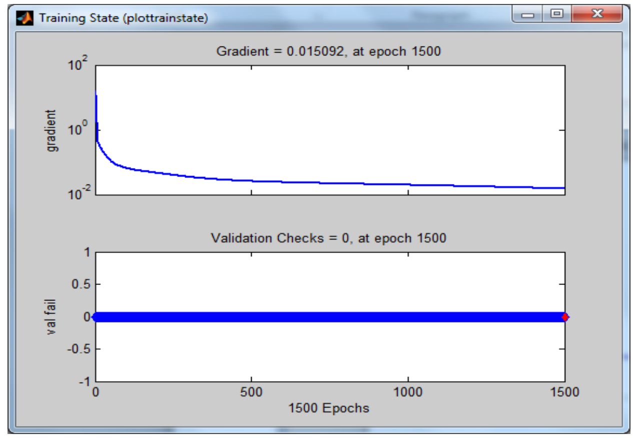


Figure.12. Validity checking of the signal samples with the variation

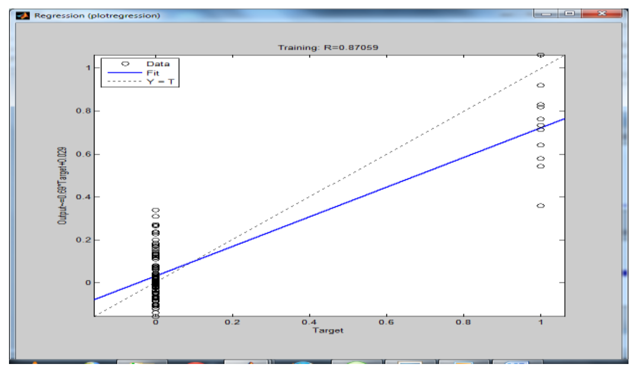
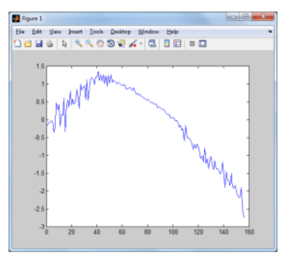
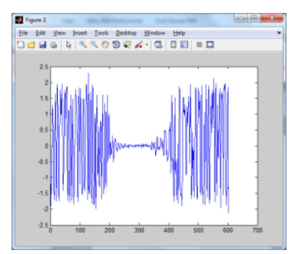
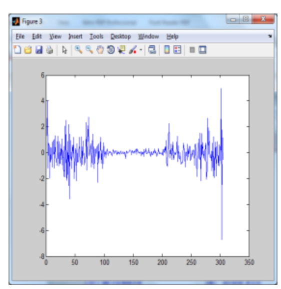


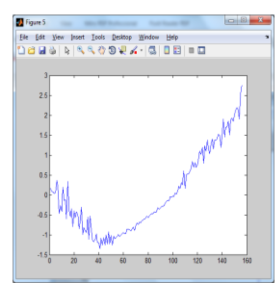
Figure. 13. Regression Models of the Signal Models with Output Training with the defined variation models





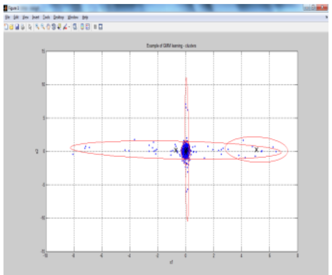
a.First level detail coefficients b.Second level detail coefficients



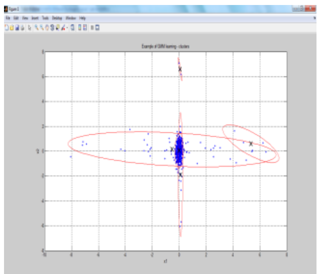


c.Third level detail coefficients d.Fourth level detail coefficients

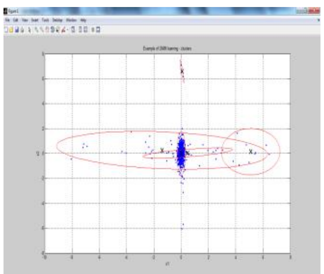
Figure.14. Wavelet output coefficients



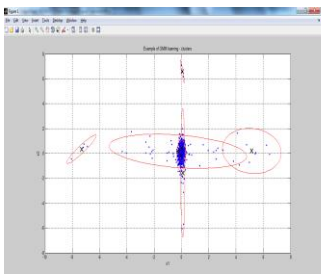
a.Undamage cable



b. Cut cable



c.Punch cable



d.Impact damage cable

Figure15. Simulated PD output obtained from GMM after training

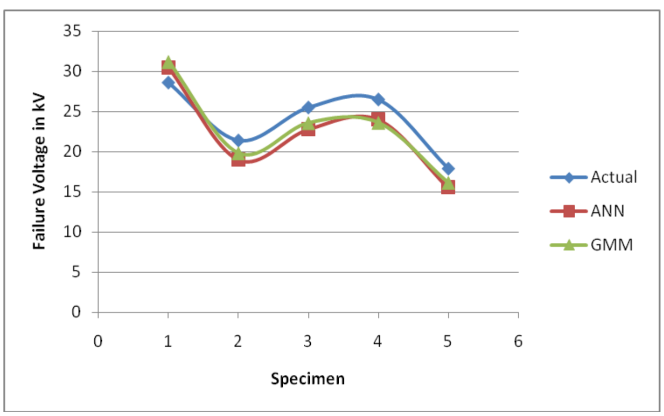


Figure.16 Comparison of ANN & GMM

6. CONCLUSION

PD analyzer is one of the best electrical equipment might be useful to determine the insulation failure for single core damaged/undamaged power cables at reasonable error margin ranging from -6.64% to 13.41% with actual failure using ANN. Whereas using GMM the obtained error margin various from -9.09% to 10.94%. From the early detection of breakdown voltage, the withstanding capacity of the cable is monitored which reduces the electrical accident. The measurement from the PD Analyzer is more accurate in cable testing. This experimental work clearly describes that the highly damaged cables can be predicted with acceptable error margin which is also validated using GMM. This test can be further extended using various other online monitoring test methods like ultrasonic, acoustic emission etc. Also, the corresponding location can be found out just before the occurrence of any fault using appropriate analysis methods. This work can also be extended using other electrical equipment like transformer, switch gears, rotating machine, etc.

Table. 1 Result analysis of XLPE cable using ANN

S.No	Type of the Specimen	PD occurance voltage (kV)	Actual Breakdown voltage(kV)	Predicted Breakdown voltage(kV) using ANN	Error in %
1	Undamaged Cable	4.5	28.6	30.5	- 6.64
2	2mm dia Punched cable	1.9	21.4	19	11
3	1 mm dia Punched cable	2.5	25.5	22.8	10.59
4	Impact Damaged cable	2.8	26.5	24	9.43
5	Hacksaw cut cable	2.3	17.9	15.5	13.41

Table. 2 Result analysis of XLPE cable using GMM

S.No	Type of the Specimen	PD occurance voltage (kV)	Actual Breakdown voltage(kV)	Predicted Breakdown voltage(kV) using GMM	Error in %
1	Undamaged Cable	4.5	28.6	31.2	- 9.09
2	2mm dia Punched cable	1.9	21.4	19.8	7.48
3	1 mm dia Punched cable	2.5	25.5	23.56	7.61
4	Impact Damaged cable	2.8	26.5	23.6	10.94
5	Hacksaw cut cable	2.3	17.9	16.1	10.06

ACKNOWLEDGMENTS

The authors would like to appreciate and acknowledge the suggestions and encouragements given by the Senior Scientists of Vikram Sarabhai Space Centre, Thiruvananthapuram, India and all the Electrical & Electronics Engineering staff of National Engineering College, Kovilpatti.

Table 3 Results of both methods and its differences

S.No	Type of the Specimen	Actual Breakdown voltage(kV)	Predicted Breakdown voltage(kV) using ANN	Predicted Breakdown voltage(kV) using GMM	Difference in kV
1	Undamaged Cable	28.6	30.5	31.2	0.7
2	2mm dia Punched cable	21.4	19	19.8	0.8
3	1 mm dia Punched cable	25.5	22.8	23.56	0.76
4	Impact Damaged cable	26.5	24	23.6	0.4
5	Hacksaw cut cable	17.9	15.5	16.1	0.6

REFERENCES

[1] Boggs S; Pathak A; Walker P; "Partial discharge XXII: high frequency attenuation in shielded solid dielectric power cable and implication thereof for PD location", IEEE Electr. Insul. Mag., 12, 1, 9-16, (1996).

[2] Fonseca Badillo M; Negrete Navarrete L; González Parada A; Castaneda Miranda A; "Simulation and analysis of underground power cables faults" Procedia Engineering, 35, 50 – 57, (2012)

[3] Redy Mardiana; Charles Q. Su; "Partial Discharge Location in Power Cables using a Phase Difference Method" IEEE Transactions on Dielectrics and Electrical Insulation 17, 6; (2010).

[4] Ahmed N.H; Srinivas N.N; "On-line partial discharge detection in cables", IEEE Transactions on Dielectrics and Electrical Insulation, 5, 2, 181–188, (1998).

[5] Mashikian, M.S; "Partial discharge location as a diagnostic tool for power cables", Power Engineering Society Winter Meeting, 2000. IEEE, 3, 1604 – 1608, (2000).

[6] Wendong Zheng; Yong Qian, Ning Yang; Chengjun Huang; Xiuchen Jiang; "Research on Partial Discharge Localization in XLPE Cable Accessories Using Multi-Sensor Joint Detection Technology" Przegląd Elektrotechniczny (Electrical Review), R. 87, NR 11,(2011).

[7] Muhamad Mansor; Prodipto Sankar Ghosh; Ahmad Basri Abdul Ghani; "PD Patterns Recognition In XLPE Cable Under Various Thermal Conditions Using Statistical Technique" IJRRAS, 5, 2, 171-181, (2010).

[8] Xiaoli Zhou; Yong Qian; Muqing Liu; "The Application of Partial Discharge Detection for the condition assessment of XLPE Power Cables" Przeglad Elektrotechniczny (Electrical Review), R. 88, NR 6,(2012).

[9] Cheng Yonghong; Chen Xiaolin; Zhang Shaofeng; Lv Yihang; "On-line Partial Discharge Monitor System of XLPE Power Cable Based on Virtual Instrument" Proceedings of the 7th International Conference on Properties and Applications of Dielectric Materials, 1, 207-210, (2003).

[10] Ahmed N. H; Srinivas N. N; "On-Line Partial Discharge Detection in Cables", IEEE Annual Report - Conference on Electrical Insulation and Dielectric Phenomena, Minneapolis, 214-217, (1997).

[11] Amjad Hussain G; Lauri Kumpulainen; Joni V.Kluss; Matti Lehtonen; "The Smart Solution for the Prediction of Slowly Developing Electrical Faults in MV Switchgear Using Partial Discharge Measurements" IEEE Transactions on Power Delivery, 28, 4, 2309-2316, (2013).

[12] Eichhorn, R. M; "Treeing in Solid Extruded Electrical Insulation", IEEE Trans. On Electrical Insulation, EI-12, 1, 2–18, (1976).

[13] Masayuki Teda; "Dielectric Breakdown Process of Polymers". IEEE Trans. On Electrical Insulation, EI-15, 3, 206–224, (1980).

[14] Kaneiwa, H; Suzuoki, Y; Mizutani, T; "Characteristics of partial discharges in artificial simulated tree channels during tree propagation", IEEE Trans. On Dielectrics and Electrical Insulation, 8, 1, 72-77, (2001).

[15] Yoon H.H; Kim J.C; Park J.C; "A neural network approach for on-line estimation of partial discharge location in power transformer using advanced correlation technique", proc.of .Int.conf.Intelligent system application to power system", 1, 316-320, (1996).

[16] Nattrass, D. A; "Partial Discharge Measurement and Interpretation" IEEE Electrical Ins. Mag. 4, 3,(1988).

[17] Ginzo Katsuta Hiroshi Suzuki; Hirotaka Eshima; Takeshi Endoh; "Discrimination of Partial Discharge from Noise in XLPE Cable Lines Using a Neural Network" IEEE Proc. of the 2nd Int. Forum on Applications Neu. Net. to Power Sys.,(1993).

[18] Suzuki H; Endoh T; "Pattern Recognition of Partial Discharge in XLPE Cables Using A Neural Network" Proc. of the 3rd Int. Conf. on Pro. and App. of Dielectric MateTokyo, Japan, (1991).

[19] Suzuki H; Endoh T; "Pattern Recognition of Partial Discharge in XLPE Cables Using a Neural Network" IEEE trans. on Electrical Insulation, 27, 3, (1992).

[20] Sivanandam S.N., Sumathi S. and Deep S.N. ‘Introduction to Neural networks using MATLAB-6.0’, Tata McGraw-Hill publishing company Ltd., New Delhi, India, (2007).

D.F.Jingle Jabha was born at Nagercoil, Kanyakumari District on 1976. She has completed U.G in NICE, Kumaracoil in Electrical and Electronics Engineering discipline and P.G in Power Electronics and Industrial Drives in Sathyabama institute of science and Technology, Chennai. Now working as a Assistant Professor in EEE department, C.S.I.Institute of Technology, Thovalai for the past 16 years, also doing research in the field of power systems at Anna University, Chennai on external basis. Have more than 6 National/International journal publications and 12 conference papers. Now working in the area of XLPE and EPDM power cables and NDT. She is having research contact with CPRI, BHEL, IISc etc.

Dr.K.Selvi was born at Madurai, Tamilnadu on 1968. She has completed U.G, P.G & Ph.D in Thiagarajar College of Engineering, Madurai. Now working as Associate Professor in Electrical and Electronics department, TCE, Madurai for the past 25 years. She is having more than 55 National/International journal publications and 50 conference papers.Now working in the area of Evolutionary algorithms, power cables and power systems. She is having research contact with various research organizations. She is a life member of various engineering societies like, ISTE and Institute of Engineers (India), Kolkatta. She has received awards for the research contribution from Science and technology and Institute of Engineers. She has organized many Workshops, Seminar and Conferences. She is having very good academic records and guiding many Ph.D/M.S students.

Dr.R.Joselin was born at Nagercoil, Kanyakumari District on 1975. He has completed U.G in J.M.I.T, Chitradurga in the mechanical Engineering discipline and P.G in computer aided design in Sathyabama institute of science and Technology, Chennai. Now working as a Professor in Mechanical Engineering department, C.S.I.Institute of Technology, Thovalai for the past 16 years, also did his research in the field of Acoustic Emission at Jawaharlal Nehru Technological University, Hyderabad. Have more than 18 National/International journal publications and 32 conference papers. Now working in the area of composite pressure vessels, power cables and NDT. He is having research contact with VSSC/ISRO, HAL etc. He has also received “young faculty award” in 2014. He has made important contributions to bring out a methodology for the burst pressure prediction of Glass Fibre Reinforced plastic (GFRP) pressure vessels. He has also proposed a model using AE parameters to predict the life of complex composite pressure vessels. He is a life member of various engineering societies like ISAMPE, ISTE and ISNT.