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Obtaining measurement patterns of partial discharges in power cables XLPE using Probabilistic Neural Networks

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Abstract- This paper presents a computational implementation of a Probabilistic Neural Network for obtaining patterns of partial discharges in power cables XLPE. The experimental measurement data of the power cables are obtained in the Laboratory Testing Equipment and Materials (LAPEM), which is a certified laboratory property of the Comisión Federal de Electricidad (CFE) in México. These data implicitly contain the patterns of partial discharges and are used to carry out the training and testing of Probabilistic Neural Network. In order to illustrate the reliability and validity of the proposed computational implementation, the results obtained by this proposed implementation are compared with those calculated by the methodologies given in the standard IEC 60270.

Index Terms- Probabilistic Neural Networks, partial discharges, power cables XLPE, pattern recognition.

I. Introduction

One of the most sensitive techniques to detect problems in the power cable isolation is the measurement of Partial Discharges (PD). However, its application is limited due to electromagnetic interference problems that occur on site, further that the partial discharge data are difficult to interpret and only trained personnel with experience can provide an accurate conclusion about abrupt changes in the nature of the insulator, which are caused by vacuoles in a solid or gas space between the surfaces of an insulator to a conductor or another insulator. The Artificial Neural Networks (ANN) has been extensively applied for classifying complex stochastic partial discharge patterns because of its ability to learn from a few trained fault examples [1,2]. However, the fundamental issue in NN learning and classification is generalization, i.e. the potential of the NN to function reliably well for some unknown or unseen PD data. Many NN topology algorithms have been applied for partial discharge classification and these include: the back-propagation (BP) algorithm [1,3–4]; the Kohonen self-organizing map and learning vector quantization [1]; modular neural networks [5]; adaptive resonance theory [6]; the counter propagation NN [7]; hidden Markov models [8]; fuzzy logic controllers [9] and more recently the probabilistic neural network [10].

The Probabilistic Neural Networks is a type of Artificial Neural Networks, which together make a very useful technique for obtaining patterns of certain phenomena associated with the partial discharges and related cases. The above is because the PNN technique has many qualities such as speed training, simulation speed, precision, plus the ability to facilitate detection of the intensities corresponding to each type of discharge, since when the measurements contain three types of partial discharges, makes it easier to understand such measurements [11].

The partial discharge activity generates both physical phenomena and chemical changes within the dielectric material, causing the transmission of acoustic, electrical and optical energy that can be detected and analysed using appropriate sensors. The acoustic technology for target detection has developed very rapidly in the past few years [12] and therefore strong tools such as signal processing and feature extraction for the detection of a partial discharge condition are required [13]. Several researchers have successfully used acoustic detection methods for studying the characteristics of electrical discharges on insulators [14]. Many signal analysis techniques have been used, such as Fourier transform [15], wavelet transform (WT) [16], as well as neural networks in order to characterize and classify the electrical discharge signals [17,18]. A partial discharge is an electrical breakdown phenomenon which is confined and located in the region of an insulating medium, emerging between two conductors which are at different potentials. Partial discharges have detrimental effects on the environment in which they occur [19]. In solid or liquid produce a slow but continuous degradation of the elements that surround them, which ends in the electrical breakdown of insulating material (internal and external PD). In gaseous medium such as air, partial discharges produce the corona effect [20]. However, the results obtained by these means led to questions regarding the effectiveness of pattern classification and recognition of partial discharges established until today, As well as questions to any treatment of this data to improve the interpretation of the phenomenon, but allowed evaluate the practical importance of deployments magnitude and phase of the pulses [21] and the analysis of waveform of partial discharge signals [22]. In [23] is presented the first study case concerning to the change of patterns of partial discharges in power cables due to the aging process, and thereby starts the diagnosis using pattern recognition.

According to the above, it is necessary to establish metrics statistics to define the type of partial discharge present in certain isolation (external, internal or surface discharge). For the development of these statistical metrics, ANN [24-28] have been of great interest to researchers because they can be used as a technology for data mining because it offers the means to model effectively and efficiently complex phenomena and large [29]. The ANN models are programmed from the data, that is, they are able to find relationships inductively (patterns) via learning algorithms based on existing data more than the fact require the help of a modeler to specify the expression of a function of their interactions [30-31].

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This work presents the relevant data associated with *Q-Φ* y *N-Q-Φ* by partial discharge measurements on site and laboratory for power cables [27]. With these data patterns, the internal and external partial discharge, and corona effect in power cables XLPE are obtained, and they are used in a computational implementation to perform data processing using Probabilistic Neural Networks. The paper is structured as follows, in Section II is presented the design of the measurement system in the LAPEM, practical computational implementation of Probabilistic Neural Networks, the network configuration and testing, whilst the results and conclusions are presented in Section III and IV, respectively. Finally, the references and biography of the paper's authors are shown.

II. Design of the measurement system

In the testing laboratory (LAPEM) a prototype developed for measurement in the power cables XLPE, as shown in Figure 2, by means of which could perform the different partial discharge measurements where data were free of noise, this in order to obtain "clean" standards, both corona discharges as partial internal and external. Also, this prototype was useful to also obtain combined data from these measurements, creating a database to characterize in a better way the artificial neural network. These data have four columns, the first of which determines the cycle, the second angle where partial discharge is presented, the third shows the electric field strength in pC and the last column indicates the current. However, in this study the second and third column to validate the proper training of the PNN was only necessary.

Figure 2. Measuring prototype built in the test lab (LAPEM).

In Figure 3, it is possible observe the magnitude internal partial discharge (pC) in the power cable XLPE, where most of the data are in the beginning of the positive and negative cycle.

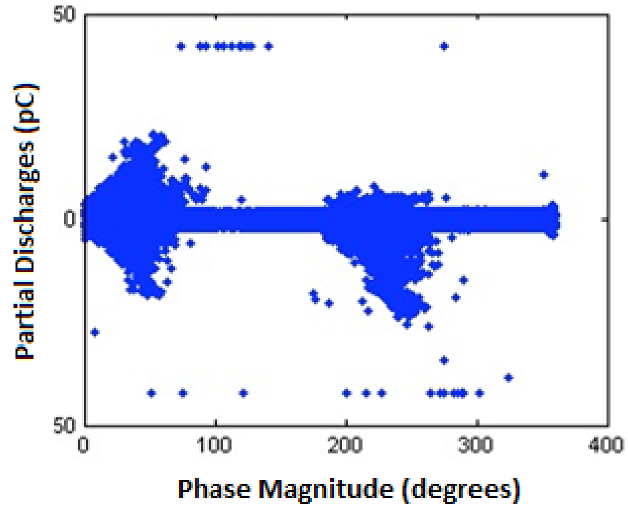

Figure 3. Internal partial discharge in power cable XLPE.

The surface partial discharges clearly are observed in Figure 4, which are created in the middle of both the positive and the negative cycle, and that have a value greater than pC internal discharges.

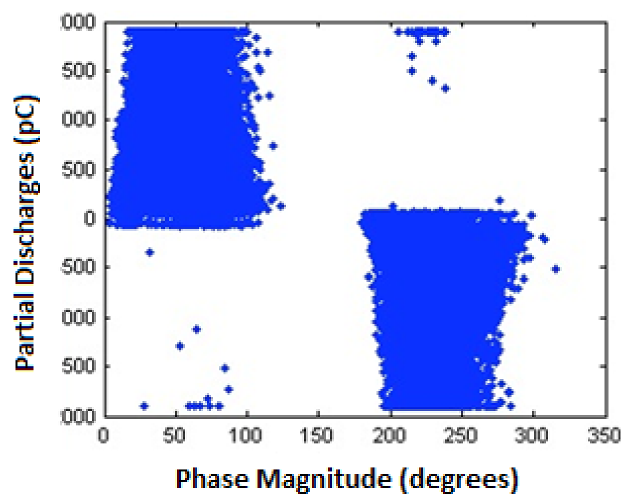

Figure 4. Surface partial discharge in cable XLPE.

Finally, the characteristics of corona measurements in power cable XLPE can be observed in Figure 5. This effect is produced in all that exists in the terminal end of the measurements.

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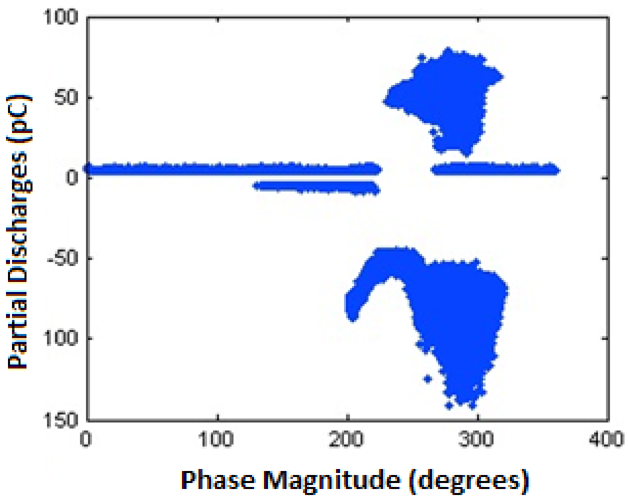


Figure 5. Corona PD measurements in power cable XLPE.

III. Development and Practical Implementation of the Proposed Probabilistic Neural Network

A. Practical implementation of Probabilistic Neural Network

The Probabilistic Neural Networks can be used in problems where it is necessary to carry out the data classification. Unlike the process used for regression problems, in which an adjustment is made of weights and bases according to the presented error; in the classification process the weights adjustment is not made and only output patterns are determined by comparing and calculating distances. Figure 6 shows the architecture of the configuration of a Probabilistic Neural Network, in which is based the RNN developed in this paper.

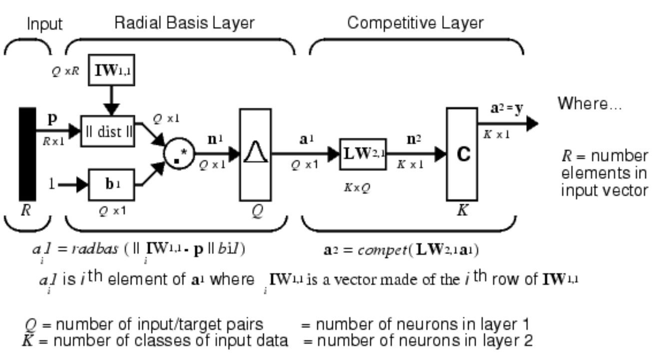


Figure 6. Architecture of the Probabilistic Neural Network.

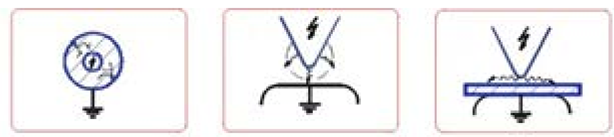
The performance of the PNN can be explained as follows, when the network is presented with an input, the first layer computes distances from the input vector to the training vectors and produces a vector whose elements indicate how close the input is detected with that of training [10]. Then the second layer sums these contributions for each class of entries seeking to produce as output a vector of probabilities. Finally, a transfer function at the output of the second layer contains the maximum of these probabilities, and produces a 1 for that class and a 0 for the other classes.

B. Network configuration

The application of neural networks in fault diagnosis has two stages, stage one is for the training process, during which the training patterns are supplied to the network to perform calculations or adjustment of some of its parameters, while stage two is the process of testing, during which delivers a known data pattern in order to verify if the output delivered by the network corresponds to the expected output.

C. Network testing

Some simulations were performed to determine the patterns extraction of PNN, using a prototype with the three possible conditions of partial discharges, as shown in Figure 7.



a) Internal DP b) Corona c) Surface PD

Figure 7. Characteristics of measurement patterns for proposal PNN.

In order to obtain a large amount of data for training of Probabilistic Neural Network, measurements were performed in the power cable XLPE considering seven replicates for each type of partial discharge. By separating the measurements for each partial discharge are obtained measurements with the following characteristics: noise-free and unmixed data. Once the data needed for the training of PNN were obtained, we proceeded to generate parameters for generating results.

IV. Results

Once the neural network has been trained and tests have been performed, the data is processed and presented as a percentage for each internal and superficial partial discharge, and to the corona and electromagnetic noise. Figure 8 shows the percentage of partial discharge in which the concentration of the data is observed with greater clarity.

From these data, a simulation is performed with the data cluster of new patterns of partial discharges to obtain the results shown in Tables 1-6. Table 1 shows the results obtained by considering the internal partial discharge pattern in which there are a lot of data of this discharge with respect to other types of PD.

Table 1. Percentages of measurements, internal DP.

Partial discharges	Percentage of PD (%)
Internal	99.2226
Surface	0
Corona	0.6478
Noise	0.1296

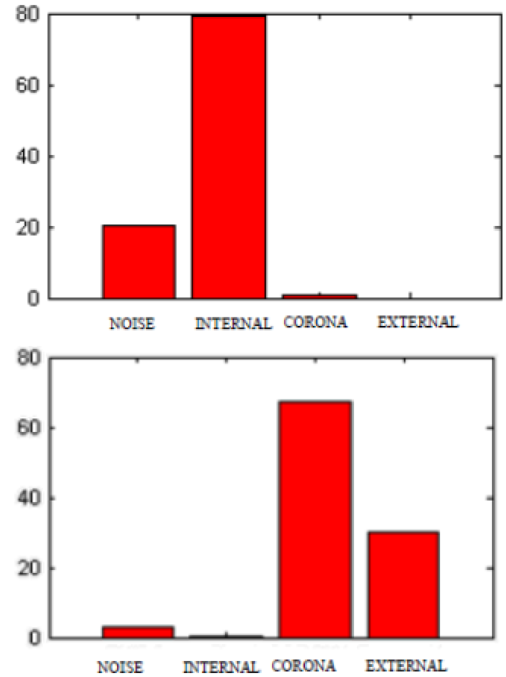


Figura 8. Percentage of each partial discharge in power cable XLPE.

Table 2 shows the results of the percentage of measurements obtained by simulation with the data pattern of the surface partial discharge. In the simulation, 93.5683% of measurements for this PD is obtained, making it possible to say that the neural network is trained properly for this pattern.

Table 2. Percentages of measurements, surface DP.

Partial discharges	Percentage of PD (%)
Internal	0
Surface	93.5683
Corona	6.35403
Noise	0.07767

Finally, we carried out the simulation for training the Probabilistic Neural Network with the corona. This training section of neural network is the most complicated of the whole process, since it is possible to determine that there mixtures in data patterns, however, in Table 3 it is shown that 89.89% of the measurements correspond to data of corona. In accordance to above mentioned, the proposed Probabilistic Neural Network is trained correctly for the case of the corona partial discharge.

Table 3. Percentages of measurements, corona DP.

Partial discharges	Percentage of PD (%)
Internal	5.90717
Surface	1.14474
Corona	89.8958
Noise	3.05229

As part of the innovation of this work, were also classified, in sections, the data packets of each type of partial discharge. From these data, it is possible to obtain the average of the magnitude of partial discharge to understand variability in the measurement. As shown in Table 4, the magnitude in concentration of internal partial discharge is 1.19 pC; with this data can be concluded that the magnitude of the charge of the partial discharge is very high and if the power cable XLPE continues energized with the nominal voltage, there may be a break in the insulation after 100 hours of operation, causing a failure of the power conductor. On the other hand, from the magnitude of the corona is determined that the cable XLPE already contains in somewhere an tip effect, which produces said measurement of corona, but is possible to determine that said magnitude is not sufficiently significant to affect the measurement, therefore the charge is not transcendental for the occurrence of an electrical fault.

Table 4. Values of the patterns of internal DP.

Partial discharges	Average of PD (pC)
Internal	1.19418
Surface	0
Corona	0.80966

Regarding the measurement of surface partial discharge, Table 5 shows that the average magnitude of the surface DP is 49.69 DP pC. This value is not very high compared to the conditions set by surface DP, thus it can be concluded that the insulation has a time of considerable lifetime. Compared with the measurement of corona, is observed that the surface partial discharge is much higher, which may affect the electrical losses in the cable. This may be an indication of the need to check the fittings and connections at terminals of the power cable.

Table 5. Values of the patterns of surface DP.

Partial discharges	Average of PD (pC)
Internal	0
Surface	49.6924
Corona	17.3337

Finally, the measurement of corona is presented in Table 6. In this table, the condition and value of the corona is very confusing due to the high values of surface discharge partial, whose magnitude could be harmful to cable insulation; whilst the value of corona and internal discharge is not harmful to the insulation, but as shown in Table 3, just 1.1% of the data correspond to surface PD. It must be pointed out that over time it is possible to have insulation breakdown in the power conductor.

Table 6. Values of the patterns of corona DP.

Partial discharges	Average of PD (pC)
Internal	2.2665
Surface	108.457
Corona	63.3199

V. Conclusions

A computational implementation based on Probabilistic Neural Networks for obtaining patterns of partial discharges in XLPE power cables has been presented. The reliability of the probabilistic neural network has been demonstrated by comparing the results obtained with the proposed neural network and those calculated with the methodologies given in IEC-60270. The reliability of the probabilistic neural network has been demonstrated by comparing the results obtained with the proposed neural network and those calculated with the methodologies given in IEC-60270. From the data, it can be concluded that the proper classification of partial discharge is not sufficient to determine the fault condition; because by the average of the partial discharge is possible to know the right characteristics to predict, by time, the parameters that will affect the safe operation of the power cable.
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References

[1] E. Gulski, A. Krivda, Neural network as a tool for recognition of partial discharges, IEEE Transactions on Electrical Insulation 28 (6) (1993) 984–1001.

[2] A. Mazroua, R. Bartnikas, M. Salama, Neural network system using the multilayer perceptron technique for the recognition of partial discharge pulse shapes due to cavities and electrical trees, IEEE Transactions on Power Delivery 10 (1) (1995) 92–96.

[3] R. Candela, G. Mirelli, R. Schifani, PD recognition by means of statistical and fractal parameters and a neural network, IEEE Transactions on Dielectrics and Electrical Insulation 7 (1) (2000) 87–94.

[4] A. Krivda, Automated recognition of partial discharges, IEEE Transactions on Dielectrics and Electrical Insulation 2 (5) (1995) 792–821.

[5] T. Hong,M. Fang, Detectionand classificationof partial discharge using a feature decomposition-based modular neural network, IEEE Transactions on Instrumentation and Measurement 50 (5) (2001) 1349–1354.

[6] B. Karthikeyan, S. Gopal, S. Venkatesh, Adaptive resonance theory 2—an unsupervised NN for PD pattern recognition and classification, Expert Systems with Applications 31 (2) (2006) 345–350.

[7] B. Freisleben, M. Hoof, R. Patsch, Using counter propagation neural networks for partial discharge diagnosis, Neural Computing and Applications 7 (1998) 318–333.

[8] L. Satish, Use of hidden Markov models for partial discharge pattern classification, IEEE Transactions on Electrical Insulation 28 (1993) 172–182.

[9] T. Abdel Galil, R. Sharkawy, M. Salama, Partial discharge pattern classification using the fuzzy decision tree approach, IEEE Transactions on Instrumentation and Measurement 54 (6) (2005) 2258–2263.

[10] D. Evagorou, A. Kyprianou, P. Lewin, Feature extraction of partial discharge signals using the wavelet packet transform and classification with a probabilistic neural network, IET Science Measurement and Technology 4 (3) (2010) 177–192.

[11] Selesnick IW. A higher density discrete wavelet transform. IEEE Trans Signal Process 2006;54:3039–48.

[12] Antonini M, Barlaud M, Mathieu P, Daubechies I. Image coding using wavelet transform. IEEE Trans Image Process 1992;1:205–20.

[13] Ramirez C, Moore P. Identification of surface discharges over new and aged polymeric chain insulators using a non invasive method. In: IEEE proceedings of the 41st international universities power engineering conference, 2006 (UPEC'06); 2006. p. 903–6.

[14] Gorur R, Chang J, Amburgey O. Surface hydrophobicity of polymers used for outdoor insulation. IEEE Trans Power Delivery 1990;5:1923–33.

[15] Nyamupangedengu C, Luhlanga L, Letlape T. Acoustic and HF detection of defects on porcelain pin insulators. In: IEEE power engineering society conference and exposition in Africa, 2007 (PowerAfrica'07), IEEE; 2007. p. 1–5.

[16] Kreuger F, Gulski E, Krivda A. Classification of partial discharges. IEEE Trans Electr Insul 1993;28:917–31.

[17] Huang C-M, Huang Y-C. A novel approach to real-time economic emission power dispatch. IEEE Trans Power Syst 2003;18:288–94.

[18] G. O. Young, "Synthetic structure of industrial plastics (Book style with paper title and editor)," in *Plastics*, 2nd ed. vol. 3, J. Peters, Ed. New York: McGraw-Hill, 1964, pp. 15–64.

[19] Méndez Albores Raúl, "Técnicas de Medición y Localización de Descargas Parciales en Transformadores. Luz y Fuerza del Centro". Pag 1 a la 70. Ed CFE. 2000.

[20] Van Brunt, R. J., "Stochastic properties of partial-discharge phenomena", IEEE Transactions on Electrical Insulation, Vol. 26, pp. 902-948, 1991.

[21] Cichecki, P., Jongen, R., Gulski, E., Smit, J.J., Quak, B., Petzold, F. and Vries, F., "Statistical Approach in Power Cables Diagnostic Data Analysis", IEEE Transactions on Dielectrics and Electrical Insulation Vol. 15, No. 6, December 2008.

[22] Cichecki, P., Jongen, R., Gulski, E., Smit, J.J., Quak, B., Petzold, F. and Vries, F., "Statistical Approach in Power Cables Diagnostic Data Analysis", IEEE Transactions on Dielectrics and Electrical Insulation Vol. 15, No. 6, December 2008.

[23] H. Ma, J.C. Chan, T.K. Saha, C. Ekanayake, Pattern recognition techniques and their applications for automatic classification of artificial partial discharge sources, IEEE Trans. Dielectr. Electr. Insul. 20 (2) (2013) 468–478.

[24] Sanz Molina Alfredo y Bonifacio Martín del Brío, "Redes Neuronales y sistemas Difusos", 2da edición, Editorial Alfaomega, 2006.

[25] M. Oskuoee, A.R. Yazdizadeh, H.R. Mahdiani, A new feature extraction and pattern recognition of partial discharge in solid material by Neural network, in: 2012 Eighth International Conference on Natural Computation (ICNC), 29–31 May 2012, 2012, pp. 183–187.

[26] S.Mohanty, S. Ghosh,Artificialneuralnetworksmodeling of breakdownvoltage of solid insulating materials in the presence of void, IET Sci. Meas. Technol. 4 (5) (2010) 278–288.

[27] Ri-cheng L, Kai B, Chun D, Shao-yu L, Guo-zheng X. Study on partial discharge localization by ultrasonic measuring in power transformer based on particle swarm optimization. In: IEEE international conference on high voltage engineering and application, 2008 (ICHVE 2008); 2008. p. 600–3.

[28] W. Yan and Kai F., "Features Selection for Partial Discharges Diagnosis", Proceedings of 12th SPIE: Health Monitoring and Smart Nondestructive Evaluation of Structural and Biological Systems IV. 2005.

[29] Ch. Kim, T. Kondo and T. Mizutani, "Change in Partial-Discharges Pattern with Aging", IEEE Transactions on Dielectrics and Electrical Insulation Vol. 11, No. 1, February 2004.

[30] "Toolbox of Artificial Neural Networks of Matlab", IEEE Transactions on Computer Aided Design of Integrated Circuits and Systems 19 No. 1, January 2000.

[31] Evagorou, D., Kyprianou, A., Lewin, P. L., Stavrou, A., Efthymiou, V. and Georghiou, G. E., "Classification of Partial Discharge Signals using Probabilistic Neural Network", 9th IEEE International Conference on Solid Dielectrics, Winchester, UK. pp. 609-615, July 2011.

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