Software Development for Partial Discharges Separation and Identification in the Presence of Multiple Partial Discharge Activities

Jansen Paula Villibor[1], Gustavo Paiva Lopes[2], Estácio Tavares Wanderley Neto[3], Matheus Penha Pereira[4], Gabriel Henrique Faria[5]

1 - High Voltage Laboratory - LAT-EFEI. Federal University of Itajubá – UNIFEI. E-mail.: jansen@lat-efei.org.br
2 - High Voltage Laboratory - LAT-EFEI. Federal University of Itajubá – UNIFEI. E-mail.: gustavo@lat-efei.org.br
3 - High Voltage Laboratory - LAT-EFEI. Federal University of Itajubá – UNIFEI. E-mail.: estacio@lat-efei.org.br
4 - High Voltage Laboratory - LAT-EFEI. Federal University of Itajubá – UNIFEI. E-mail.: matheus@lat-efei.org.br
5 - High Voltage Laboratory - LAT-EFEI. Federal University of Itajubá – UNIFEI. E-mail.: gabriel@lat-efei.org.br

Recebido em: 17/04/2024 Revisado em: 05/11/2024 Aprovado em: 12/12/2024

Abstract: This work presents a software development for measuring, separating, and identifying partial discharges (PD) for conventional and non-conventional measurement systems. To validate the PD sources with the T-F Map (Time-Frequency Map), the results of the new software confront the results of commercial software with PD measurements on the stator winding of a rotating machine with a conventional PD measurement system. By selecting clusters (groups of data) in the T-F Map, the software rebuilds these clusters into new PRPD (Phase Resolved Partial Discharge) sub-patterns. The results of the PD sources separation step are equivalent to the results of the commercial system, allowing to proceed to PD identification. The PD identification mechanism consists of a Fuzzy Inference System (FIS) in conjunction with Machine Learning (ML) techniques. This paper employs a commercial PD simulator that provides three typical PD sources: - corona, superficial, and internal, to validate the PD identification process. The results from the developed PD identification mechanism, validated with the commercial PD simulator, achieved optimum likelihood values (close to 100%), allowing the conclusion that the PD identification mechanism was satisfactory in the carried-out analyses.
Key-words: Software Development. Conventional Measurement System. Unconventional Measurement System. Partial Discharges Separation. Partial Discharges Identification.

Resumo: Este trabalho apresenta o desenvolvimento de um software para medição, separação e identificação de descargas parciais (PD) para sistemas de medição convencional e não-convencional. Para validar a separação de múltiplas fontes de PD com o T-F Map (Mapa de Tempo-Frequência) os resultados obtidos com o novo software são confrontados com os resultados de um software comercial em medições realizadas no estator de uma máquina rotativa com um sistema de medição convencional de descargas parciais. Ao selecionar clusters (grupos de dados) no T-F Map, o software reconstrói estes clusters em novos sub-padrões PRPD (Padrão de Descargas Parciais em Resolução de Fase). Os resultados obtidos na etapa de separação mostraram-se equivalentes aos resultados obtidos com o sistema comercial, permitindo proceder para a etapa de identificação do tipo da descarga parcial. O mecanismo de identificação consiste em um Sistema de Inferência Fuzzy (FIS) em conjunto com técnicas de Aprendizado de Máquinas (ML). Este artigo empregou um simulador de PD comercial que fornece três tipos básicos de PD: - corona, superficial e interna, para validar o processo de identificação de descargas parciais. Os resultados obtidos com mecanismo de identificação desenvolvido e validado com o simulador comercial apresentou valores de *likelihood* considerados ótimos (próximos de 100 %), permitindo concluir que o mecanismo de identificação de PD foi satisfatório nas análises realizadas.
Palavras-chave: Desenvolvimento de Software. Sistemas de Medição Convencional. Sistemas de Medição Não-Convencional. Separação de Descargas Parciais. Identificação de Descargas Parciais.

Introduction

The International Electrotechnical Commission in the IEC 60270 High-voltage test techniques - Partial discharge measurements, defines partial discharge as a localized electrical discharge that only bridges the insulation between conductors and may or may not occur adjacent to a conductor (IEC 60270, 2015). In general, partial discharges (PD) are caused by electrical stress in the insulation or on its surface (Gockenbach, 2013).

The decades of 1950 and 1960 testify to the development of knowledge in the PD area which led to the establishment of correlations between PD activities and their specific degradation mechanisms and breakdown (Kemp, 2007).

Since 1960, the PD measurement based on the electrical method has been widely accepted as a diagnostic tool to evaluate the insulation quality of high-voltage equipment (Hauschild, Lemke, 2014). Generally, PD measurements are required as part of acceptance tests for most medium and high-voltage equipment in the industry (Cigre Brochure 662, 2016).

PD measurements are typically non-destructive and can be applied to monitoring and evaluating the equipment's insulation since it starts to operate (Ragusa et al. 2022; Shahsavarian et al., 2021).

The PRPD pattern is one of the first techniques to separate and identify partial discharge sources (Fruth, Fuhr, 1990). However, in the presence of multiple PD sources and noises, classifying the different PD phenomena with PRPD can be unfeasible due to the overlap of various phenomena, making it necessary to apply PD separation techniques such as the T-F Map.

Separating and identifying PD sources is not a trivial task (Cruz et al., 2022; Duan et al., 2019; Karimi et al., 2020; Montanari, Seri, 2018; Sánchez, 2020; Seri et al., 2021; Yu, Song, 2003).

Resources like the T-F Map can be a valuable resource, for multiple PD sources separation, without heavy computational cost. Since the application of artificial intelligence (AI) for PD identification began, many techniques have been developed to achieve robust, reliable, and general identification results.

AI methods can be separated into two basic categories: classical machine learning methods and deep learning (DL) based methods.

The classical ML methods are for the most part composed of artificial neural network (ANN), support vector machine (SVM), k-nearest neighbors (KNN), fuzzy inference system, decision tree (DT), and random forest (RF) (Soltani, El-Hag, 2019; Firuzi et al., 2019, Hussein et al., 2017; Mas'ud et al., 2017; Soltani, Shahrtash, 2019).

DL methods are for the most part composed by deep neural network (DNN), as the autoencoder (AE), convolutional neural network (CNN), recurrent neural network (RNN), and, deep belief network (DBN) (Lu et al., 2020)

In the previous context, the development of a software capable measuring, separating, and identifying PD in the presence of different partial discharge activities, for conventional and unconventional PD measurement systems, can be a valuable contribution to this research area.

Partial Discharge Measurement Systems, Prpd Pattern and The T-F Map

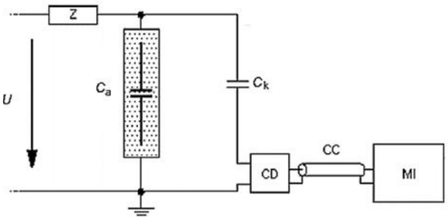
Conventional Partial Discharge Measurement System

The conventional partial discharge measurement systems for apparent charge measurements can be divided into three main subsystems: coupling device, transmission system (connection cables), and measuring instrument (IEC 60270, 2015).

The coupling device is an integral part of the test circuit measurement system, and its components are designed to obtain optimum sensitivity in a specific test circuit. Usually, it is a four-terminal (quadrupole) network that converts input current signals to output voltage signals. The signals captured by the coupling device are lead to the measuring instrument through the transmission system.

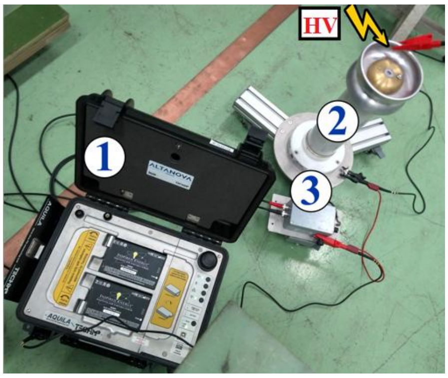
Figure 1 shows the measuring circuit with a coupling device (CD) in series with the coupling capacitor (Ck), where U is the applied voltage, Z is a filter, Ca is the capacitance of the equipment under test, CC is the cable connection, and MI is the measuring instrument.

Figure 1 – Setup for partial discharge measurements in accord with IEC 60270 standard IEC 60270, 2015).



In this paper, to validate the PD separation methodology, the data acquired with TechImp conventional, were used. The system is composed of a coupling capacitor, coupling device (measuring impedance), transmission system (cables), and the measurement instrument Aquila, which is a portable measuring device, Figure 2.

Figure 2 – TechImp conventional PD measurement system: 1 = PD measurement instrument (Aquila); 2 = Coupling capacitor; 3 = Coupling device (quadrupole).



Unconventional Partial Discharge Measurement System

Unconventional PD measurements, such as HFCT (High-Frequency Current Transformer) applications, are very useful where it is not possible to de-energize the equipment. Connected to the ground conductor, an HFCT can provide significant information about the PD activities on site.

To validate the software identification, measurements with an HFTC were made at a PD Simulator, capable of providing three different types of PD sources: corona, internal, and surface. The PD signal came from an HFCT connected to the ground of the PD Simulator. Figures 3 and 4 show an HFCT and the PD Simulator.

Figure 3 – HFCT.

Figure 4 – PD Simulator.

The PRPD Pattern and the T-F Map

One of the worldwide techniques to assess the probable source of partial discharges in electrical apparatus is through the analysis of the PRPD pattern (Cacciari, Contin, Montanari, 1995; Cavallini et al., 2002; Cavallini, Montanari, Pulleti, 2003; Cavallini, Montanari, 2005; Contin, Montanari; Ferraro, 2000). The PRPD pattern is a two-dimensional chart that relates the PD pulse magnitude, usually in Coulombs, but which can also be presented in Volts, with the phase angle of the alternating excitation voltage.

Reference PRPD patterns are widely available for different types of defects and equipment, mainly for the conventional method (IEC 60270) of measuring partial discharges. The Cigré technical brochure 676, Partial Discharges in Transformers, produced by the working group D1.29, brings in its Annex 10 a collection of variations of measured PRPD pattern (Cigre Brochure 676, 2017).

In the presence of multiple PD sources, classifying the different PD phenomena by the PRPD pattern can be compromised by the overlap of these phenomena, being necessary to apply PD separation techniques such as the T-F Map.

The T-F Map is an approach to separate the multiple sources of PD in a measurement. This method relies on the premise that different PD sources have different pulse waveforms, which have different features of equivalent time duration and equivalent bandwidth (Bartnikas, Novak, 1993; Cavallini et al., 2003a; Cavallini, et al. 2003b; Cavallini, Montanari, 2005; Cavallini et al., 2010; Contin et al., 2002).

For a PD pulse (p) with N samples, the time reference, t_0, is defined as (1), where t_i

represents the acquisition time of pulse sample i.

$$t_0 = \frac{\sum_{i=0}^{N} t_i p_i(t_i)^2}{\sum_{i=0}^{N} p_i(t_i)^2} \quad (1)$$

The equivalent time duration of a single pulse of partial discharge is defined by equation (2):

$$T_{eq} = \sqrt{\frac{\sum_{i=0}^{N} (t_i - t_0)^2 p_i(t_i)^2}{\sum_{i=0}^{N} p_i(t_i)^2}} \quad (2)$$

The Fourier Transform translates signals from the time domain to the frequency domain, representing the signal by combining sine and cosine functions. For a time-domain signal (p), its Fourier transform is defined by (3), where t and ξ denote time and frequency, respectively:

$$\mathcal{F}\{p(t)\} = P(\xi) = \int_{-\infty}^{+\infty} p(t) e^{-i2\pi\xi t}\, dt \quad (3)$$

If P is the frequency obtained from the Fourier Transform, then the equivalent bandwidth of a partial discharge pulse can be determined by equation (4), where f_i represents the frequency in the pulse sample i:

$$F_{eq} = \sqrt{\frac{\sum_{i=0}^{N/2} (f_i)^2 |P_i(f_i)|^2}{\sum_{i=0}^{N/2} |P_i(f_i)|^2}} \quad (4)$$

The T-F Map is built by projecting T_{eq} and F_{eq} of each PD pulse onto a two-dimensional plane in which the projected points belonging to PD pulses with similar patterns will merge to form a distinct cluster. This way, several groups can be clustered, and each group must correspond to a single source of partial discharge.

This method provides a mechanism that can individually describe the PD pulse in terms of its time and frequency representation, being a powerful tool to separate different PD sources and improve insulation diagnosis accuracy. Figure 3 illustrates the PRPD pattern, and Figure 4 the corresponding T-F Map.

Figure 5 – The PRPD pattern representation.

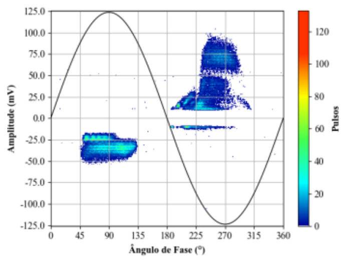
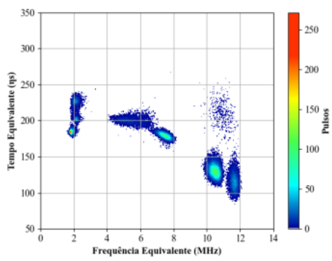


Figure 6 – The corresponding T-F Map of the PRPD of Figure 3.



Partial Discharge Software Development

The development of the software consists of three main parts: measurement and signal processing, PD separation, and PD identification.

To measure PD pulses in the range of nanoseconds with a good representation of his shape implies in hardware with high sample rate, and reasonable vertical resolution, beyond the two channels, one for the applied voltage and the other for the PD pulses. After surpassing these hardware requirements, the acquired signals pass through the application of signal processing techniques, that enable the application of a passband filter, pulse extraction to build the T-F Map, and PD pulse peak time of occurrence to correlate with the applied voltage and construct the PRPD pattern.

Figure 7 brings the initial user interface during the measurement with the developed software, with the instantaneous oscillogram of the PD pulses, the signal FFT (Fast Fourier Transform), measured quantities, and the dynamic PRPD and TF-Map.

Figure 7 - Software user interface during PD measurements.

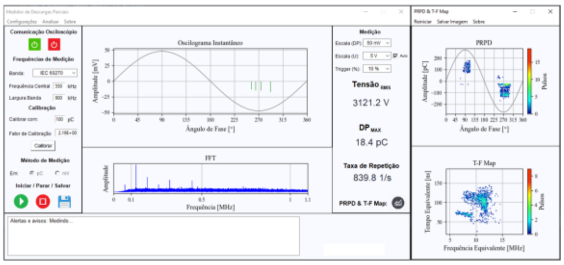
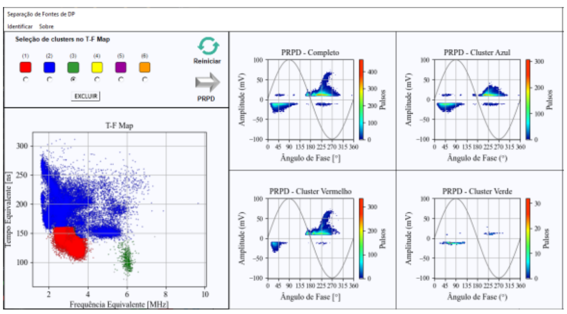


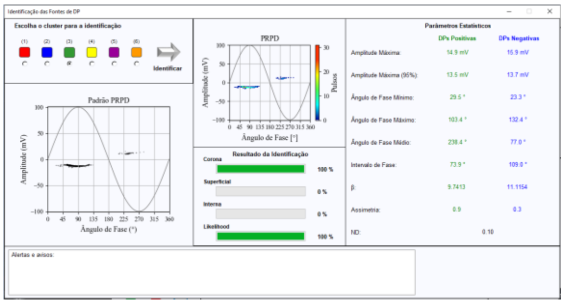
Figure 8 brings the user interface during the PD separation with the T-F Map, the user interacts with the interface, selecting clusters on the T-F Map and the code re-build the data in the PRPD sub-patterns for the number of selected clusters.

Figure 8 – Software user interface during PD separation.



For PD identification, the software combines a Fuzzy Inference System and Machine Learning to identify the PD source. In this last step, the interface allows the user to filter undesirable data before going to identification, **Erro! Fonte de referência não encontrada.** shows the user interface during the PD identification. In this PD identification interface, the software brings the type of partial discharge, the likelihood of the identification, and some statistical parameters extracted from the analysis.

Figure 9 - Software user interface during PD identification.



Pd Separation Validation With Rotating Machines Measurements

This section will present the results of the validation of the PD separation methodology of the developed software by comparing the separation results with commercial software, the TechImp PDPro.

The PD measurement is used validate the separation mechanism with the PD measurements on an 11 kV generator stator winding. The PD measurements were carried out with a coupling capacitor connected to the equipment under test. Figure 10 brings a partial view of the 11 kV stator winding.

Figure 10 – Partial view of the stator winding (Villibor et al., 2022).

Figure 11 and Figure 12 bring the PRPD pattern and the corresponding T-F Map for the PD measurement over the stator winding.

Figure 11 – Complete PRPD pattern from the PD measurement on the stator winding.

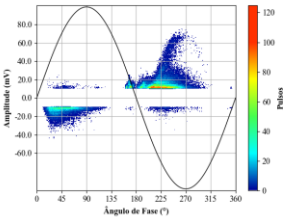
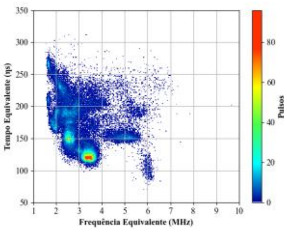


Figure 12 – Corresponding T-F Map of the PRPD in Figure 11.



To the T-F Map of Figure 12, a selection of three clusters (with approximately the same data points) was made in both software to compare the PRPD sub-patterns that will be built with the PD data inside each cluster (red, blue, green). Figures 13 and 14, bring the clusters on T-F Map selected in each software.

Figures 15 and 16 bring the PRPD sub-patterns after filtering unnecessary data for the blue cluster in Figures 13 and 14, respectively.

Figure 13 – T-F Map with cluster separation: blue, red, and green, with the developed software.

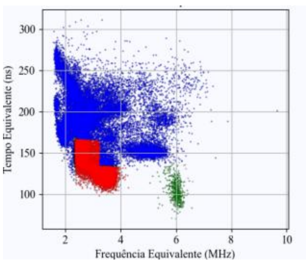


Figure 14 – T-F Map with cluster separation: blue, red, and green, with TechImp PDPro (Villibor et al., 2022).

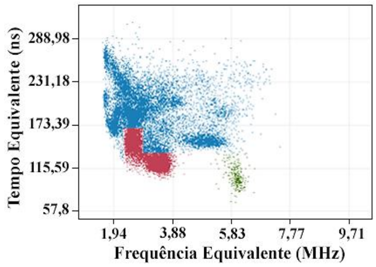


Figure 15 – PRPD pattern of the blue cluster with the developed software.

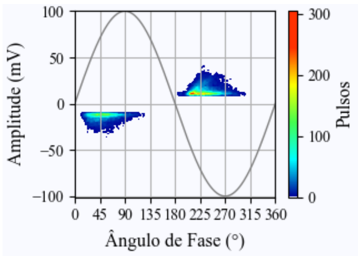
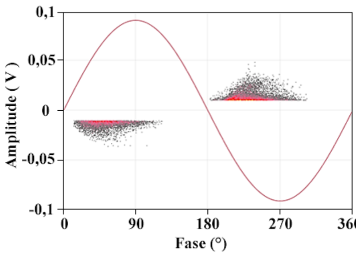


Figure 16 – PRPD pattern of the blue cluster with TechImp PDPro (Villibor et al., 2022).



The blue cluster in Figures 13 and 14 are discharges produced by internal voids distributed along the insulation, characterized by the symmetry between the positive and negative PD, rounded shape, and typically with negative PD between 0° and 90°, and positive PD between 180° and 270° (IEC 60034-27-2, 2012).

Figures 17 and 18 bring the PRPD sub-patterns after filtering unnecessary data for the red cluster in Figures 13 and 14, respectively.

Figure 17 – PRPD pattern of the red cluster with the developed software.

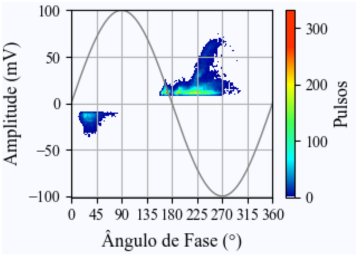
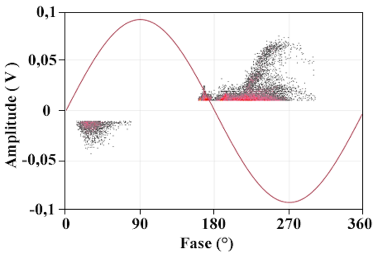


Figure 18 – PRPD pattern of the red cluster with TechImp PDPro (Villibor et al., 2022).



The red cluster in Figures 13 and 14 is probably corona activity at the slot coating and stress grading coating, characterized by an asymmetry in favor of positive discharges, occurring during the negative voltage half-cycle, combined with a rounded shape (Hudon, Bélec, 2005; Iec 60034-27-2, 2012; Montanari, 2017).

Figures 19 and 20 bring the PRPD sub-patterns after filtering unnecessary data for the green cluster in Figures 13 and 14, respectively. The green cluster of Figures 13 and 14 is a classic corona discharge PRPD pattern.

Figure 19 – PRPD pattern of the green cluster with the developed software.

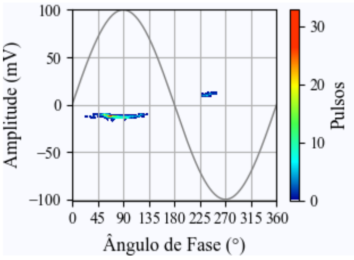
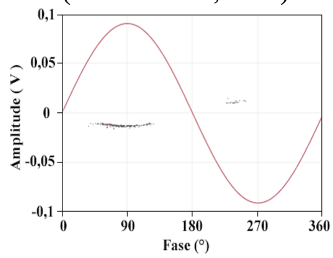


Figure 20 – PRPD pattern of the green cluster with TechImp PDPro (Villibor et al., 2022).



For all the clusters (red, blue, and green), it is possible to visually verify that the PRPD sub-patterns built after the separation process for the developed software are approximately the same PRPD sub-patterns built with the commercial software of TechImp. These results show the PD separation process of the developed software is as powerful as the PDPro.

With a resource such as the T-F Map built-in in the developed software, the PD analyses can be significantly simplified by separating overlapped PD sources, enriching the PD analysis in the presence of multiple partial discharge sources.

Pd Identification Validation With Partial Discharge Simulator

To validate the PD identification process of the developed software, measurements with the TechImp PD Simulator were made. The PD

Simulator can provide the three main types of partial discharges: corona, superficial, and internal. In this section, the measurements were performed directly with the developed software with hardware connected to the output of the PD simulator, using an HFCT, with simultaneous corona and internal discharges.

Figure 21 and Figure 22 bring the complete PRPD and the corresponding T-F Map obtained with measurement with simultaneous corona and internal discharges.

Figure 21 – Complete PRPD pattern from the PD measurement with the PD Simulator.

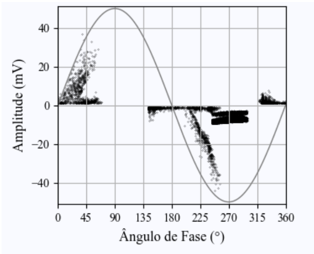


Figure 22 – Corresponding T-F Map of the PRPD in Figure 21.

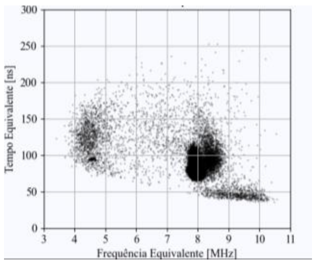
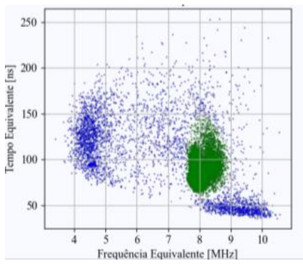


Figure 23 brings the T-F Map of Figure 22 with cluster selection. The two clusters selected manually are in the colors blue and green.

After the selection of the clusters, the data of each cluster pass through filtering undesirable data and then the PRPD sub-patterns (Figures 24 and 25) of each cluster (blue and green) are collected and the identification algorithm analyzes the data providing the diagnostics of the type of partial discharge for each cluster selected.

Figure 23 – T-F Map of Figure 22 with cluster selection: blue and green.



The PD in Figure 24 was identified as corona discharges. In the PD Simulator, the electrodes that produce the corona discharges have a point-to-plane configuration, with the high voltage connected to the point electrode. With this configuration and measurements with the HFCT, it is expected that the PD have negative polarity with low dispersion for the PD amplitudes. Also, in cases that are not affected by the memory effect, it is expected that the mean value of the phase angle to be around the voltage peak as in Figure 26, around 270°.

Figure 24 – PRPD pattern of the green cluster of Figure 23.

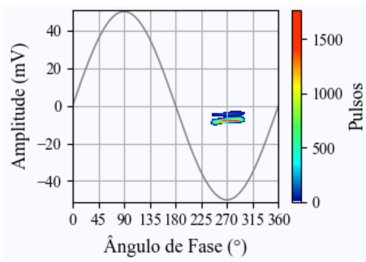


Figure 25 – PRPD pattern of blue cluster of Figure 23.

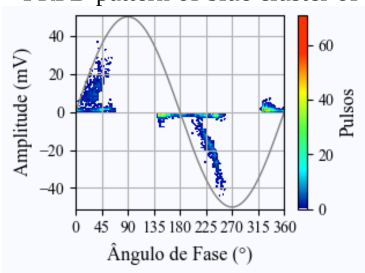


Figure 26 shows the results of the PD identification with the developed software for the PRPD in Figure 24.

Figure 26 – The result of the identification (corona discharges) for the PRPD pattern from the green cluster of Figure 24.

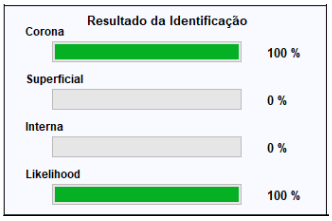
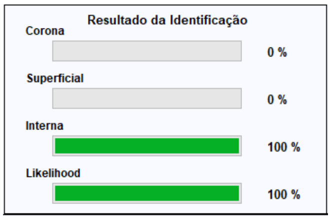


Figure 27 shows the results of the PD identification with the developed software for the PRPD in Figure 25.

Figure 27 – The result of the identification (internal discharges) for the PRPD pattern of Figure 26.



The PD in Figure 25 was identified as internal discharges. Internal discharges can be significantly affected by memory effects that can advance or delay the PD events. This leads to negative values for the minimum phase angle value.

Internal PD affected by the memory effect has a large phase interval, higher than 100°. Another characteristic of internal PD is the occurrence of higher dispersion in the PD amplitudes.

The likelihood in Figures 26 e 27 is the sum of the output membership functions of each type of PD considered, in this case, three types: corona, internal, and surface, ordinarily, equal to one (100 %). Low values of likelihood indicate that PD passing through is partially new to the software identification knowledge base.

For both PD types: internal and corona, the results were reliable to the type of PD source in the measurement, with high values of likelihood (equal to one).

Conclusions

The work presented the main steps for the development of one new software for PD measurement, multiple PD sources separation, and, identification.

The main steps of the development were validated with real equipment measurements (PD separation) and with a partial discharge simulator (PD identification).

Quantitatively and qualitatively, the results achieved with the software can be considered satisfactory, as the separation algorithm could achieve, practically, the same results as the commercial TechImp software, and PD identification could distinguish between the main types of partial discharges: corona, internal, and superficial.

Regarding the PD identification, at this first moment, due to the lack of a large database, the goal was to identify the main types of partial discharges.

Further research needs to be made to create a bigger database that could englobe the PD sources of different electrical apparatus, defect dimensions, and additional information that could improve the generality of the developed software identification algorithm embracing many types of PD sources.

Acknowledgment

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES).

References

BARTNIKAS, R.; NOVAK, J. On the character of different forms of partial discharges and their related terminology. IEEE Transactions on Dielectrics and Electrical Insulation. V. 28, p. 956-968, 1993.

CACCIARI, M.; CONTIN, A.; MONTANARI, G. C. Use of a mixed-weibull distribution for the identification of partial discharge phenomena. IEEE Transactions on Dielectrics and Electrical Insulation. V. 2, p. 614 - 627, 1995.

CAVALLINI, A.; MONTANARI, G. C.; PULLETI, F.; CONTIN, A. Advanced PD inference in on-field measurements. Part II: Identification of defects in solid insulation systems. IEEE Transactions on Dielectrics and Electrical Insulation. V. 10, p. 528-538, 2003a.

CAVALLINI, A.; MONTANARI, G. C.; CONTIN, A.; PULLETI, F. A new approach to the diagnosis of solid insulation systems based on PD signal inference. IEEE Electrical Insulation Magazine. V. 19, p. 23-30, 2003b.

CAVALLINI, A.; MONTANARI, G. C. A new methodology for the identification of PD in electrical apparatus: Properties and Applications. IEEE Transactions on Dielectrics and Electrical Insulation. V. 12, p. 203-215, 2005.

CAVALLINI, A.; CHEN, X.; MONTANARI, G. C.; CIANI, F. Diagnosis of EHV and HV transformers through an innovative partial-discharge-based technique. IEEE Transactions on Power Delivery. V. 25, p. 814-824, 2010.

CONTIN, A.; MONTANARI, G. C.; FERRARO, C. Partial-Discharge source recognition by weibull processing of the pulse-height distributions. IEEE Transactions on Dielectrics and Electrical Insulation. V. 7, p. 48-58, 2000.

CONTIN, A.; CAVALLINI, A.; MONTANARI, G. C.; PASINI, G.; PULETTI, F. Digital detection and fuzzy classification of partial discharge signals. IEEE Transactions on Dielectrics and Electrical Insulation. V. 9, p. 335-348, 2002.

CONTIN, A.; PASTORE, S. Classification and separation of partial discharge signals by means of their auto-correlation function evaluation. IEEE Transactions on Dielectrics and Electrical Insulation. V. 16, p. 1609-1622, 2009.

CRUZ, J. S.; FRUETT, F.; LOPES, R. R.; TAKAKI, L. F.; TAMBASCIA, C. A.; LIMA, E. R.; GIESBRECHT, M. Partial discharges monitoring for electric machines diagnosis: A Review. Energies. V. 15, N.° 21, Art. N.° 7966, 2022.

DUAN L.; HU, J.; ZHAO, G.; CHEN, Z.; HE, J. WANG, S. X. Identification of partial discharge defects based on deep learning method. IEEE Transactions on Power Delivery. V. 34, p. 1557–1568, 2019.

FIRUZI, K.; VAKILIAN, M.; PHUNG, B. T.; BLACKBURN, T. R. Partial discharges pattern recognition of transformer defect model by LBP & HOG features. IEEE Transactions on Power Delivery. V.34, p. 542-550, 2019.

FRUTH, B.; FUHR, J. Partial discharge pattern recognition - A tool for diagnosis and monitoring of ageing, In CIGRE SESSION, 1990.

GOCKENBACH, E. Partial discharge measuring techniques. In: RYAN, H. M. (Org.). High-voltage Engineering and Testing. p. 599-614. London, United Kingdom: The Institution of Engineering and Technology (IET), 2013.

HAUSCHILD, W.; LEMKE, E. High-Voltage Test and Measuring Techniques, 1. Ed. Berlin: Springer, 2014. 518p.

HUDON, C.; BÉLEC, M. Partial discharge signal interpretation for generator diagnostics. IEEE Transactions on Dielectrics and Electrical Insulation. V. 12, p. 297-319, 2005.

HUSSEIN, R.; SHABAN, K. B.; EL-HAG, A. H. Robust feature extraction and classification of acoustic partial discharge signals corrupted with noise. IEEE Transactions on Instrumentation and Measurement. V. 66, p. 405–413, 2017.

INTERNATIONAL ELECTROTECHNICAL COMMISSION. IEC 60034-27-2: Rotating electrical machines - part 27-2: On-line partial discharge measurements on the stator winding insulation of rotating electrical machines. Geneva, 2012.

INTERNATIONAL ELECTROTECHNICAL COMMISSION. IEC 60270: High-voltage test techniques - partial discharge measurements. Geneva, 2015.

KARIMI, M.; MAJIDI, M.; MIRSAEEDI, H.; AREFI, M. M.; OSKUOEE, M. A novel application of deep belief networks in learning partial discharge patterns for classifying corona surface and internal discharges. IEEE Transactions on Industrial Electronics. V. 67, p. 3277–3287, 2020.

KEMP, I. J. Partial Discharge and Their Measurement. In: HADDAD, A.; WARNE, D. (Orgs.) Advances in High Voltage Engineering. p. 139–190. London, United Kingdom: The Institution of Engineering and Technology (IET), 2007.

LU, S.; CHAI, H.; SAHOO, A.; PHUNG, B. T. Condition monitoring based on partial discharge diagnostics using machine learning methods: A comprehensive state-of-the-art review. IEEE Transactions on Dielectrics and Electrical Insulation. V. 27, p. 1861-1888, 2020.

MAS'UD, A.A.; ARDILA-REY, J. A.; ALBARRACÍN, R.; MUHAMMAD-SUKKI, F., BANI, N. A. Comparison of the performance of artificial neural networks and fuzzy logic for recognizing different partial discharge sources. Energies. V. 10, p. 1060, 2017.

MONTANARI, G. C.; SERI, P.; A partial discharge-based health index for rotating machine condition evaluation. IEEE Electrical Insulation Magazine. V. 34, p. 17–23, 2018.

MONTANARI, G. C. Time behavior of partial discharges and life of type II turn insulation specimens under repetitive impulse and sinusoidal waveforms. IEEE Electrical Insulation Magazine. V. 34, p. 17-26, 2017.

RAGUSA, A.; SASSE, H. G.; DUFFY, A. On-line partial discharge localization in power cables based on electromagnetic time reversal theory – numerical validation. IEEE Transactions on Power Delivery. V. 37, p. 2911-2920, 2022.

SÁNCHEZ, A. S.; GÓMEZ, F. A.; ROMERO C. A. V; SERNA, J. M. R. Separation of partial discharge sources measured in the high-frequency range with HFCT sensors using PRPD-teff patterns. Sensors, V. 20, N.° 2, Art. N° 382, 2020.

SERI, P.; GHOSH, R; MONTANARI, G. C. An unsupervised approach to partial discharge monitoring in rotating machines: Detection to diagnosis with reduced need of expert support. IEEE Transactions on Energy Conversion. V. 36, p. 3485-2492, 2021.

SHAHSAVARIAN, T.; PAN, Y.; ZHANG, Z.; PAN, C.; NADERIALLAF, H.; GUO, J.; LI, C; CAO, Y. A review of knowledge-based defect identification via PRPD patterns in high voltage apparatus. IEEE Access. V. 9, p. 77705-77728, 2021.

SOLTANI, A.A.; EL-HAG, A. H. Denoising of radio frequency partial discharge signals using artificial neural network. Energies. V. 12, p. 3485, 2019.

SOLTANI, A.A.; SHAHRTASH, S.M. A pattern recognition based method for optimum decomposition level determination in wavelet transform for noise reduction of partial discharge signals. IET Science, Measurement & Technology, V. 14, p. 9-16, 2020.

VILLIBOR, J. P.; MARQUES, B. P.; LOPES G. P.; ARREGALO, R.; JUNIOR, R. G. O.; CAIXETA. P. H. Aplicação prática da ferramenta T-F map na separação de descargas parciais em máquinas rotativas e cabos de média tensão. In Simpósio Brasileiro de Sistemas Elétricos, 2022.

YU, H.; SONG, Y. H.; Using improved self-organizing map for partial discharge diagnosis of large turbogenerators. IEEE Transactions on Energy Conversion. V. 18, p. 392–399, 2003.