Electric Power Systems Research 136 (2016) 398–405

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

Partial discharges location in transformer winding using wavelets and Kullback–Leibler divergence

Daniel Guillen[a], Gina Idarraga-Ospina[a,*], Enrique Mombello[b], Sergio Cabral[c]

[a] Programa Doctoral de Ingeniería Eléctrica (DIE), Universidad Autónoma de Nuevo León (UANL), San Nicolás de los Garza, N.L. Mexico
[b] Instituto de Energía Eléctrica (IEE), Universidad Nacional de San Juan (UNSJ), San Juan, Argentina
[c] Mestrado en engenharia elétrica, Universidade Regional de Blumenau (FURB), Blumenau, Brazil

ARTICLE INFO

Article history:
Received 18 May 2015
Received in revised form 17 January 2016
Accepted 12 March 2016

Keywords:
Partial discharges
PD location
Transformer windings
Discrete wavelet transform (DWT)
Kullback–Leibler (KL) divergence

ABSTRACT

A new algorithm to partial discharges (PD) location in transformer windings by means of the discrete wavelets transform (DWT) and the Kullback–Leibler (KL) divergence is presented. When the insulation system of transformers has considerable damage, high levels of PD appear. A PD analysis will help to prevent and to avoid catastrophic faults in the transformer insulation system, and is also useful to quantify the damage level into it. However, it is a complex task, because PD signals have a small magnitude and are presented during some microseconds. In this paper, a lumped parameter model RLC is used to model the transformer winding and to obtain PD reference signals. The DWT is used to process those signals. PD location is finally estimated by means of the minimum entropy concept that minimizes the Kullback–Leibler (KL) divergence between PD signals (test and reference signals). Different time durations and amplitudes to the PD signals were considered. The results of computer simulation confirm the accuracy of the proposed algorithm, with an error less than 5%. Also, the algorithm is validated in a distribution transformer winding.

1. Introduction

Transformer windings suffer different types of stress such as mechanical, electrical, and chemical, among others. High levels of those give as a result major degradation into the insulation system. As a matter of fact, high levels of partial discharge (PD) appear when the insulation system has considerable damage, for that, PD in power transformers are widely studied precisely because are linked to the insulation system faults. Moreover, PD monitoring is used to diagnostic and to quantify damage in the transformer insulation system [1,2]. An early detection and location of PD in transformers can be useful to implement corrective actions, due to it has been reported as the second cause of failure [3], and to avoid that the power transformer can be out of services in an unexpected moment. Moreover, recurrent or periodic monitoring of the transformer is essential to guaranty the useful life of it. It is a fact that the reliability of the results will be directly related to the techniques used to asses their condition [4–6].

Several electrical methods in both time and frequency domains have been developed to detect and to locate PD in transformer windings; e.g. in [7] correlation technique in time domain is applied to PD location in transformer windings. Also, this technique is combined with the DWT, where detail (also called wavelet) coefficients are used to estimate the PD location [8]. However, these methods have their own limitations, so that in [9] a new algorithm in the frequency domain is proposed, in order to improve the time domain limitations.

Moreover, in [10] a neuro-fuzzy technique is presented for locating PD signals in power transformer, which uses unsupervised pattern recognition. In addition, other works have been developed for locating PD in transformer windings, e.g. in [11] a new technique based on series resonance frequencies is presented. In this way, transfer functions per section to PD location have been utilized in other researches [12–14]. However, these methods can be affected by noise, which limits their reliability and accuracy. By this reason, denoising processes have been included in some works, e.g. in [15] an adaptive morphological filter is applied to estimate the PD location in transformer windings.

A new algorithm to PD location is developed in this paper, where the algorithm is evaluated at different noise conditions and validated in a distribution transformer winding. Signal processing is carried out in time domain using the discrete wavelet transform

* Corresponding author. Tel.: +52 8113404020x5997.
E-mail addresses: guillenad@gmail.com (D. Guillen), gidarraga@gmail.com (G. Idarraga-Ospina), mombello@iee.unsj.edu.ar (E. Mombello), scabral@furb.br (S. Cabral).

http://dx.doi.org/10.1016/j.epsr.2016.03.020
0378-7796/

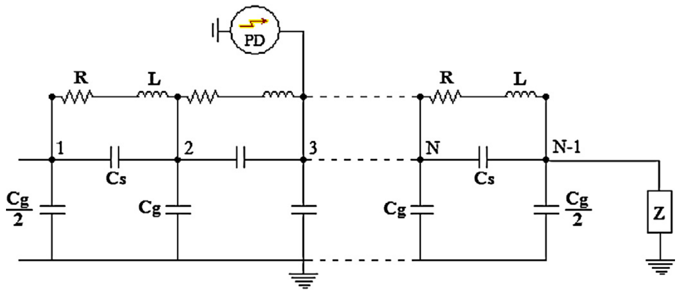

Fig. 1. Winding transformer model (*R* is the series resistance of the winding, *L* is the series inductance of the winding, *Cs* is the series capacitance, *Cg* is the capacitance to ground of the winding (turn-to-earth)).

(DWT), so as a new methodology to PD location is introduced based on a modification of the minimum Kullback–Leibler (KL) divergence called KL-modified. The proposed algorithm uses a ladder network for modeling the transformer winding. Moreover, a model for injecting PD signals between winding sections is also proposed. The algorithm requires PD reference signals which will be used to estimate the PD location, so that PD pulses in parallel along each winding section and between winding sections are analyzed. The results of computer simulation validated with measurements in a transformer winding confirm the accuracy of the proposed algorithm.

2. Transformer winding model

Winding modeling has been widely studied for analyzing internal voltage distribution in transformers, as well as other fast transient phenomena like partial discharges. As a matter of fact, the most used models for modeling a transformer winding are the lumped RLC detailed model and the multiconductor transmission line (MTL) model, each one with its own limitations and advantages, as well as its frequency range of validation [16].

This work is aimed at evaluating partial discharges along different transformer winding locations in order to estimate the PD position. The analysis is performed using a single transformer winding modeled by a ladder network with lumped parameters *R*, *L* and *C*, which is shown in Fig. 1 [17]. Although the used model has its own frequency limitations, this model is well suited for locating PD pulses in transformer windings [18], and it is used to simulate them in parallel along each winding section and also between winding sections. Moreover, the proposed method is validated by comparing the obtained simulation results with measurements in a distribution transformer winding.

In Fig. 1, each circuit section represents a disc of the transformer winding, i.e. it has N sections if there is $N+1$ nodes. When there is a PD pulse in a transformer winding, it produces signals that will be captured at the neutral terminal using an impedance circuit Z. Due that the proposed method requires PD reference signals, these signals are obtained from a calibration process according to [19].

In order to obtain the calibration signals and to show the viability of the proposed methodology, the transformer winding model parameters are taken from [20], which has 10 sections and its parameters per section (disk) are $L = 180\,\mu\text{H}$, $R = 1.2\,\Omega$, $Cs = 13\,\text{pF}$, $Cg = 3000\,\text{pF}$.

3. PD signals in windings

In practice the PD signal waveform cannot be handled easily, however, several PD effects can be analyzed using basic circuit models. In order to be able to adjust the pulse characteristics, in

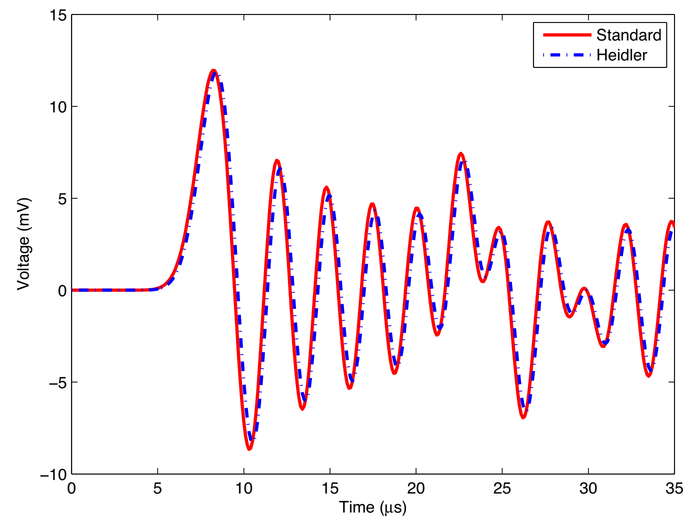

Fig. 2. Comparison between the standard calibration and Heidler function.

this work the PD pulse is characterized by the Heidler function, which is described as follows [21]:

$$S_{PD}(t) = A\left(\frac{t}{t+T_f}\right)^n e^{-(t/\tau)} \tag{1}$$

where A is the amplitude of the PD signal, T_f is the rise time or front duration, τ is the time where the function amplitude has fallen 37% of its peak value and n is a factor influencing in the exponential function. For instance, if there is a PD pulse at section 3 of the winding (see Fig. 1), its response will be captured at the neutral terminal using the impedance circuit presented in [22].

The proposed algorithm should be calibrated theoretically and experimentally, so that the obtained information can be used as a numerical template [23]. The calibration process is carried out using the Alternative Transient Program (ATP/EMTP) software [24], so that a PD pulse is injected in parallel at each section of the winding. In fact, the Heidler function is used to model the PD pulse form and the calibration has an equivalent charge of 50 pF regarding to the standard calibration. This is shown in Fig. 2 where the obtained signals are quite similar with a slight phase shift. This shows that the use of the Heidler function is advantageous in order to handle the PD pulse characteristics.

Due to the proposed algorithm requires PD reference signals for each winding sections, these signals are obtained from simulations using the following data to Heidler function: $A = 327\,\mu\text{A}$, $T_f = 1\,\text{ns}$, $\tau = 200\,\text{ns}$ and $n = 2$. For instance, if a PD pulse is simulated at sections 1,2 and 3 of the transformer winding, the obtained PD reference signals are presented in Fig. 3; these signals are used to estimate the PD location, and are quite similar in each section, making more complex the PD location. Therefore, some researches are focused on this subject with the aim to know PD signal propagation characteristics, so as its damping factors due to the position of occurrence, among others [22]. In this sense, the proposed algorithm uses the information of PD reference signals with the aim to improve the PD location and to overcome the limitations of the algorithms in time domain.

4. Discrete wavelet transform

Signal processing for PD location in transformer windings is carried out using the DWT, which has been introduced for locating PD in windings by Naderi et al [25]. Despite of the fact that the WT is considered as a very good tool for PD signal processing there are still some trial and error in its application. In this paper, its coefficients

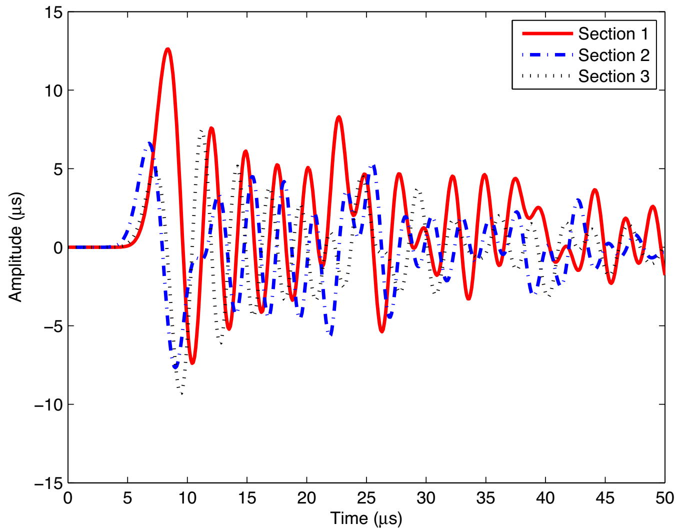

Fig. 3. Obtained PD signals for a PD pulse simulated at sections 1, 2 and 3.

will be used as input in the KL divergence, which will locate the PD, to avoid this issue.

DWT is divided in approximation (cA) and wavelet coefficients (cW). Then, a PD signal can be scaled using 3 decomposition levels as shown in Fig. 4.

Approximation and wavelet coefficients are obtained from filtering operations as follows [26]:

$$cA_j(k) = \sum_{i=0}^{N_f-1} L(i)cA_{j-1}(2k-i)$$
$$cW_j(k) = \sum_{i=0}^{N_f-1} H(i)cA_{j-1}(2k-i) \tag{2}$$

where L is the low-pass filter, H is the high-pass filter and N_f is the number of filter coefficients. Before computing the DWT, decomposition level J must be defined. More details about DWT can be found in [27].

The optimal decomposition level (J) is defined by the proposed maximum Shannon entropy as follows:

$$H_j = \frac{H_{cA}^j H_{cW}^j}{H_{cA}^j + H_{cW}^j} \tag{3}$$

where H_{cA} and H_{cW} are the Shannon entropies to the approximation and wavelet coefficients respectively, and j takes values from 1 up to J.

The proposed maximum Shannon entropy is used to obtain the maximum decomposition level, in order to reduce the discriminatory information. It is also used to avoid that the results will be affected by the selected mother wavelet, and to guarantee the proper performance of the proposed algorithm.

The Shannon entropy is given by [28]:

$$H = -\sum_{k=1}^{m} p(x_k)\ln p(x_k) \tag{4}$$

where $p(x_k)$ is computed using the energy of its corresponding coefficients, defined by:

$$p(x_k) = \frac{cA^2{}_j(k)}{\sum_{k=1}^{m} cA^2{}_j(k)} \tag{5}$$

Once the optimal decomposition level is determined, the DWT is computed and the approximation coefficients are used to determine the PD location using the KL divergence.

5. Kullback–Leibler divergence

KL divergence is a logarithmic distance measured between two-probability mass functions $p(x)$ and $q(x)$ defined by [29]:

$$D_{\mathrm{KL}}(p||q) = \sum_{k=1}^{m} p(x_k)\log\frac{p(x_k)}{q(x_k)} \tag{6}$$

where $p(x)$ and $q(x)$ are obtained using DWT coefficients according to (5). KL divergence will be zero if $p(x) = q(x)$, the smallest value of the KL divergence will be used to estimate the PD location in transformer windings.

D_{KL} is not symmetric; therefore it is proposed to use D_{KL} in its symmetric way as:

$$S_{\mathrm{KL}}(p||q) = \frac{D_{\mathrm{KL}}(p||q) + D_{\mathrm{KL}}(q||p)}{2} \tag{7}$$

The minimum value of S_{KL}, between a measured PD signal and the reference signals will be used to estimate the PD location. However, S_{KL} may or may not produce values higher than 1 and taking into account that the divergence values between 0 and 1 are preferred, a second term is proposed in order to reduce the divergence value and to avoid wrong results in the PD location. Hence, the proposed equation is:

$$\beta_{\mathrm{KL}}(i) = \frac{1}{2}S_{\mathrm{KL}}(p||q_i) + \frac{1}{2(N-1)}\sum_{\substack{j=1\\ j\neq i}}^{N}\left(\frac{S_{KL}(p||q_j)}{\sum S_{KL}(p||q_i)}\right)^2 \tag{8}$$

where p is determined using a PD signal with unknown position and q_i is defined by each PD reference signal that were previously obtained.

According to (8), the first term is associated with the real PD position and the second term contains information about other positions for making sure the PD location is well estimated. Therefore, KL-modified divergence will produce higher values when the captured PD signal is far from the PD source (real position).

6. Proposed algorithm

The optimal decomposition level must be previously determined using (3), to apply the DWT. Then, the DWT is computed for all PD reference signals, the obtained coefficients will replace those reference signals. Therefore if there is a PD pulse in any section of the winding, the captured signal is processed using the DWT and its approximation coefficients are used to compute the KL divergence regarding to each PD reference signal. Finally, the PD location along the transformer winding is estimated using the KL-modified divergence, described by (8). The flowchart of the proposed algorithm can be seen in Fig. 5.

7. Analysis of the proposed algorithm

The proposed algorithm is tested with different PD pulses simulated in parallel along the transformer winding sections using the Heidler function. A sampling frequency of 10 MHz is used, with a time window of 0.3 ms and 3001 samples. Two mother wavelets (MW) of the Daubechies family are chosen to compute the DWT, in particular Daubechies 7 ($db7$), which has proved to be the best wavelet for analyzing PD signals with damped oscillations [30].

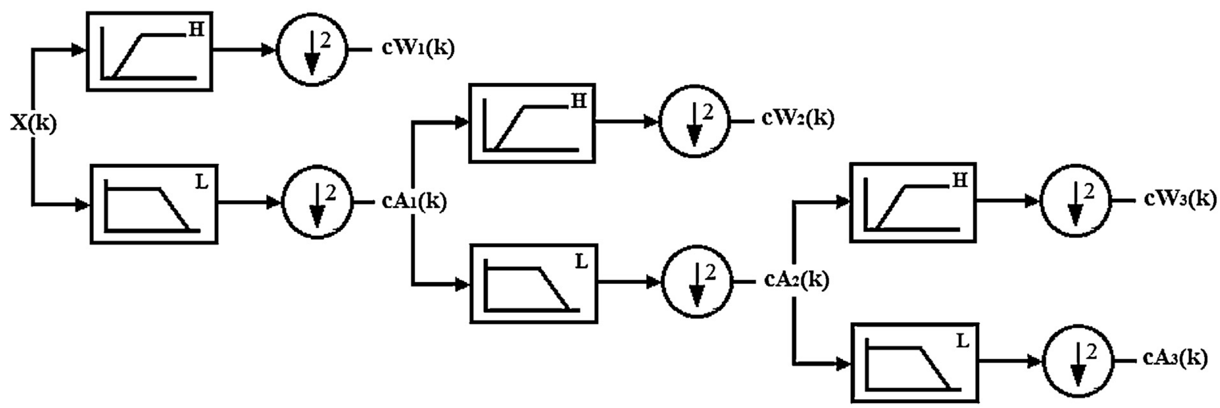

Fig. 4. Wavelet decomposition levels.

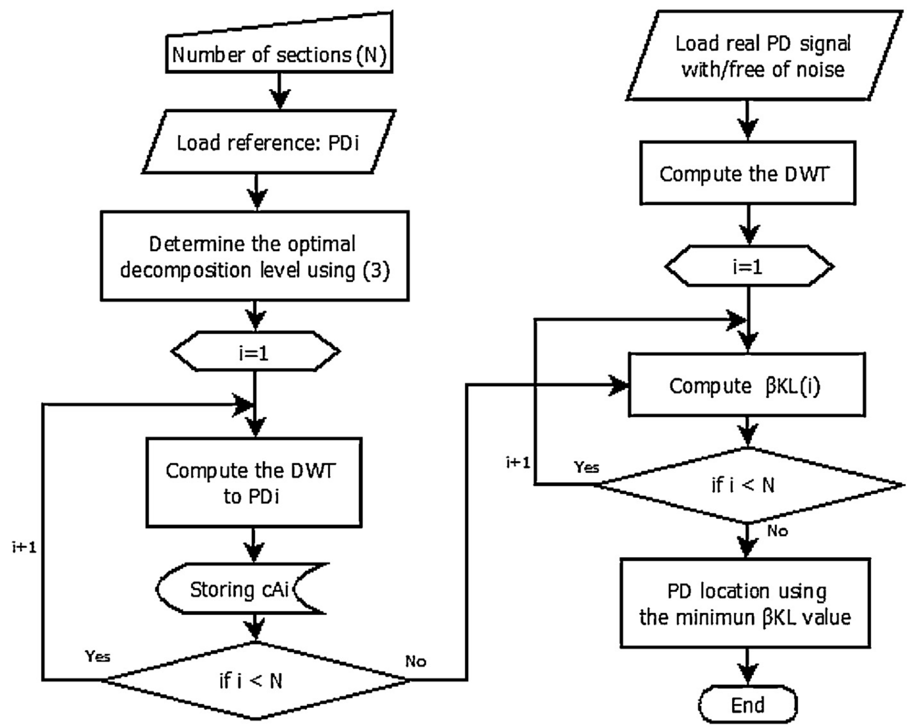

Fig. 5. Algorithm to PD location in transformer windings.

Table 1
Shannon entropies at each scale.

Scale	Wavelet *db*7			Wavelet *db*8		
	H_{cA}	H_{cW}	H	H_{cA}	H_{cW}	H
1	5.037	1.626	1.229	5.042	1.379	1.083
2	4.373	1.091	0.873	4.390	1.348	1.031
3	3.747	3.007	**1.668**	3.789	2.865	1.631
4	3.187	3.256	1.610	3.329	3.210	**1.634**
5	2.752	2.015	1.163	3.031	2.045	1.221
6	2.618	1.264	0.852	2.750	1.556	0.994
7	2.209	1.366	0.844	2.567	1.480	0.939

Also, Daubechies 8 (*db*8) is selected because it has been applied in PD detection under noise conditions [31].

To know the optimal decomposition level, PD reference signals are analyzed using the aforementioned wavelets and the Shannon entropy defined by (3). For each decomposition level, entropies results are shown in Table 1, the maximum entropy defines the optimal decomposition level, for *db*7 and *db*8 the optimal level is 3 and 4, respectively.

In order to evaluate the proposed algorithm, PD pulses were simulated along each section of the winding and the captured signals at the neutral terminal are used as PD signals. Results are presented in Table 2, where each column has the KL-modified divergence value (β_{KL}) between a PD signal (PD pulse simulated at specific position) and each PD reference signal. Then, if a PD pulse is simulated at section 5, its corresponding KL divergence values are shown in column 5, the minimum value is 0.272, which indicates the PD location. Consequently, the authors conclude that proposed algorithm produces satisfactory results for PD signals free of noise.

It has to be taken into account that, if the decomposition level is not the optimal, results of the proposed algorithm may be affected, as shown in Table 3, corresponding to PD signals without noise. Therefore, it is possible to conclude that PD location results using the KL divergence are only affected when is chosen a decomposition level greater than the optimal.

Table 2
KL divergence regarding to each PD reference.

PD reference signal	PD signal injected at section "j"									
	1	2	3	4	5	6	7	8	9	10
	Divergence β_{KL}									
1	**0.272**	0.971	1.000	1.199	1.383	1.911	2.556	2.994	3.315	6.362
2	0.739	**0.356**	0.649	1.072	1.200	1.697	2.112	2.794	3.092	5.687
3	0.812	0.834	**0.258**	0.947	0.754	1.358	1.710	2.143	2.681	4.959
4	1.190	1.011	1.039	**0.218**	0.607	0.897	1.438	1.949	2.954	4.733
5	1.229	1.165	1.042	1.008	**0.272**	0.606	0.794	1.375	1.894	4.136
6	1.773	1.696	1.341	1.172	0.974	**0.286**	0.886	0.936	1.534	3.383
7	2.334	1.994	1.658	1.414	1.001	0.941	**0.273**	0.750	1.248	2.716
8	2.802	2.525	2.183	2.057	1.325	1.090	0.784	**0.218**	0.664	1.818
9	3.479	3.194	2.842	2.772	2.121	1.642	1.074	0.761	**0.204**	1.066
10	8.390	7.522	6.617	6.030	5.101	4.147	3.307	2.280	1.164	**0.163**

Table 3
PD location at different scales.

Scale	% Localization	
	*db*7	*db*8
1	100	100
2	100	100
3	100	100
4	80	100
5	90	70
6	50	50
7	70	70

The proposed algorithm was tested with PD signals and different noise to signal ratio (SNR), located along the transformer winding and between winding sections. Results for PD signals simulated at different winding sections are presented in Table 4, e.g. if there is a PD at section 1 of the winding, the captured PD signal at the neutral terminal is mixed with −8 dB of noise, so that the PD signal is processed using wavelet *db*7 and the minimum KL divergence is 0.973 regarding to *PD reference 1*. At the same case, using *db*8 as the MW, the PD location was accurate, because the minimum KL divergence value obtained was 0.912. It is possible to conclude that the proposed algorithm gives satisfactory results for these cases.

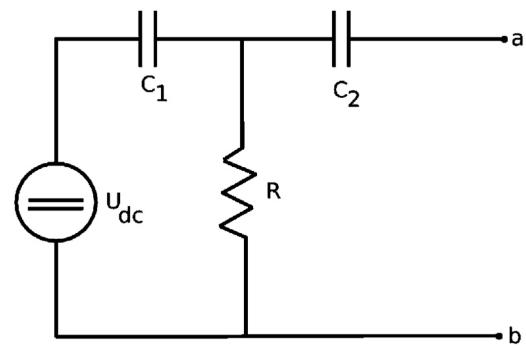

Fig. 6. Circuital arrangement for PD signals waveform between sections.

To test the algorithm with PD pulses between winding sections, it is necessary to obtain the same PD waveform used to design the algorithm, i.e. the Heidler function waveform. In this sense, the circuital arrangement shown in Fig. 6 is proposed in this work, it is the one which was implemented in the laboratory. In order to obtain the reference signals between winding sections, the PD model is connected between nodes $k-1$ and k. In this model, the capacitance C_2 represents the injected apparent charge to the transformer

Table 4
PD signals with noise along the winding sections.

PD reference signal	PD signal injected at section "i"									
	1	2	3	4	5	6	7	8	9	10
	Noise level (dBs) and wavelet *db*7									
	−8	−6	−4	−2	5	9	11	13	17	22
1	**0.973**	1.198	1.046	1.205	1.392	1.877	2.591	3.023	3.276	6.353
2	1.419	**0.855**	1.057	1.112	1.224	1.723	2.137	2.781	3.048	5.703
3	1.383	1.126	**0.617**	0.999	0.764	1.418	1.718	2.136	2.649	4.971
4	1.599	1.250	1.192	**0.419**	0.635	0.903	1.458	1.970	2.921	4.740
5	1.445	1.275	1.079	1.098	**0.300**	0.650	0.809	1.402	1.866	4.146
6	1.422	1.428	1.319	1.236	0.974	**0.316**	0.857	0.933	1.523	3.381
7	1.595	1.235	1.226	1.271	1.027	0.959	**0.288**	0.755	1.253	2.728
8	1.641	1.390	1.381	1.402	1.292	1.117	0.800	**0.227**	0.642	1.825
9	1.595	1.652	1.652	1.514	1.692	1.418	0.895	0.756	**0.208**	1.068
10	1.911	2.135	1.900	2.193	2.707	2.043	2.057	2.239	1.221	**0.160**
	Wavelet db8									
1	**0.912**	0.880	1.087	1.677	1.763	2.058	1.939	2.135	2.356	6.336
2	1.364	**0.861**	0.740	1.966	1.631	2.058	2.021	2.573	2.686	6.243
3	1.506	1.220	**0.528**	1.056	0.894	1.549	1.485	1.913	2.178	5.524
4	2.335	2.335	1.007	**0.317**	0.425	1.633	1.622	2.201	2.418	5.011
5	2.746	2.665	1.709	1.438	**0.293**	0.563	0.786	1.394	1.590	4.185
6	2.612	2.152	1.436	2.449	0.529	**0.198**	0.420	1.496	1.791	3.875
7	2.826	2.915	2.163	2.597	1.142	0.912	**0.277**	0.552	0.955	2.407
8	2.675	2.601	2.328	2.866	1.659	2.289	0.712	**0.181**	0.701	2.054
9	2.177	2.638	2.168	2.415	1.904	2.298	0.961	0.816	**0.238**	0.740
10	2.611	3.211	2.370	2.813	3.290	3.553	2.585	2.814	1.208	**0.146**

Table 5
PD signals with noise between winding sections.

PD reference signal	PD signal injected between sections "i-k"									
	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8-9	9-10	10-11
	Noise level (dBs) and wavelet *db*7									
	−10	−7	−5	−3	−1	5	8	11	15	20
1-2	**1.460**	1.061	1.027	0.884	1.502	1.781	1.330	2.126	3.895	8.179
2-3	1.605	**0.898**	1.085	1.074	1.372	1.289	1.219	2.056	3.511	7.289
3-4	1.746	1.158	**0.573**	0.867	1.105	1.259	1.046	1.505	2.999	6.119
4-5	1.536	1.277	1.164	**0.468**	1.094	1.178	0.967	1.233	2.489	5.451
5-6	1.765	1.321	1.297	1.018	**0.427**	0.933	0.985	1.237	1.868	4.573
6-7	1.551	1.225	1.379	1.007	1.057	**0.269**	0.694	0.989	1.666	3.650
7-8	1.497	1.138	1.190	1.199	1.118	0.997	**0.255**	1.044	1.093	2.648
8-9	1.763	1.445	1.249	1.178	1.213	0.911	0.728	**0.202**	0.886	1.661
9-10	1.577	1.429	1.522	1.354	1.134	1.404	0.706	0.897	**0.161**	1.186
10-11	1.979	1.682	1.900	1.675	1.807	2.464	1.386	1.295	0.748	**0.199**
	Wavelet db8									
1-2	2.033	1.723	1.658	1.800	1.787	2.258	2.195	3.699	6.340	9.189
2-3	2.046	**1.286**	1.935	1.075	1.256	1.586	1.357	2.943	5.578	8.743
3-4	**1.752**	1.589	**1.241**	1.605	1.678	1.548	1.920	2.640	4.909	7.009
4-5	2.383	1.554	1.954	**0.802**	0.871	0.835	1.011	1.712	3.957	6.351
5-6	2.020	1.588	1.718	1.152	**0.822**	1.039	0.908	1.540	3.135	5.237
6-7	2.716	1.885	2.123	1.226	1.143	**0.228**	0.977	0.821	2.636	3.986
7-8	1.843	1.861	1.991	1.166	1.429	0.835	**0.400**	1.155	1.536	2.971
8-9	2.248	2.165	2.243	2.038	2.009	0.568	1.235	**0.149**	1.220	1.930
9-10	1.768	2.656	1.678	2.506	2.067	2.065	1.660	1.084	**0.361**	0.527
10-11	2.142	3.245	2.100	3.300	2.511	2.581	1.899	1.333	0.583	**0.091**

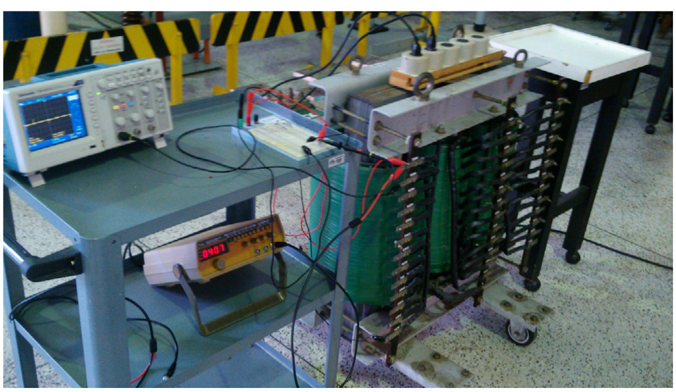

Fig. 7. Test system.

winding, whilst the parameters C_1 and R are used to define the PD signal waveform.

In Table 5, results for PD pulse simulated between winding sections are shown, e.g. if there is a PD signal between winding sections 7-8, the captured signal is mixed with Gaussian noise of 8 dB, the minimum KL divergence value using *db*7 is 0.255, and it can be seen that PD location is well estimated.

For high levels of noise, the PD location may be affected, e.g. when a PD signal is simulated between winding sections 1-2, adding −10 dB of noise, its position is wrong estimated using *db*8, such as is shown by the minimum KL divergence value (1.752), which corresponds to PD *reference 3-4*. In other cases, PD location is estimated with accuracy.

The accuracy percentages for locating PD between winding sections are 100% and 90% using *db*7 and *db*8, respectively. However, noise levels less than −10 dB may or may not affect the reliability of the proposed algorithm, in this way the authors conclude that the proposed algorithm is able to produce satisfactory results for a noise level greater than −10 dB. In fact, other applications showed that a noise level of −10 dB is a good value for evaluating the PD in a noisy environment [26].

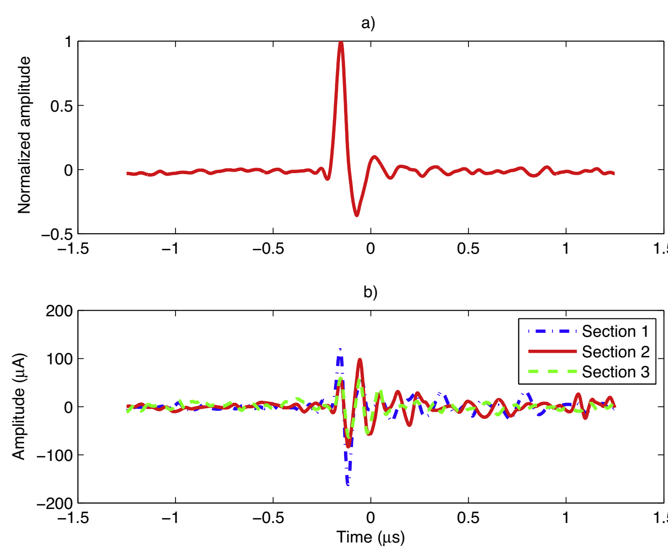

Fig. 8. Signals: (a) input PD pulse and (b) measured PD signals.

In consequence, the presented results are very attractive and the authors conclude that MW *db*7 gives better results than WM *db*8 for PD signals with noise. However, both wavelets produce similar results for PD signals without noise.

Finally, the DWT reduces the information to be analyzed during PD location and is equal to total samples divided by 2^j. Hence, the results allow concluding that the proposed algorithm can be applied for PD location in transformer windings (off-line process) under noise conditions.

8. Experimental results

To validate the algorithm, a three-phase distribution transformer of 51.96 kVA and continuous discs is used. Further, each transformer winding has 13 taps and each tap is taken as a winding section, such as is shown in Fig. 7.

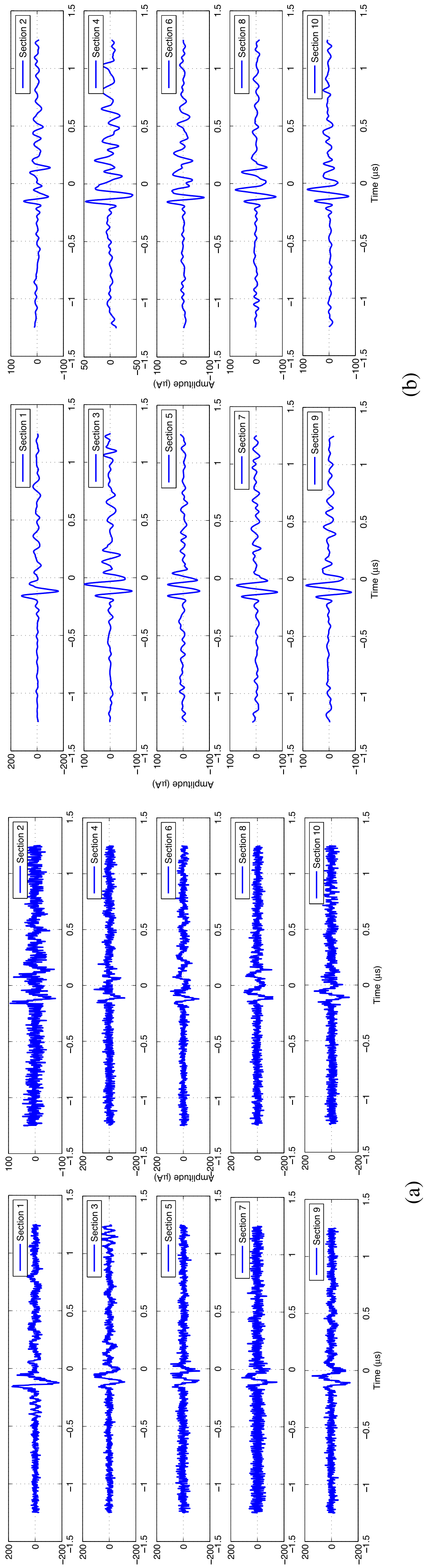

Fig. 9. (a) Measured signals with noise and (b) Measured-filtered signals.

Table 6
Experimental results for PD location.

Scale	% Localization			
	Along each section		Between winding sections	
	Mother wavelet			
	*db*7	*db*8	*db*7	*db*8
2	100.00	100.00	100.00	100.00
3	100.00	100.00	100.00	100.00
4	100.00	100.00	100.00	100.00
5	100.00	91.67	100.00	100.00
6	50.00	83.33	66.67	66.67
7	25.00	8.33	16.67	16.67
8	25.00	25.00	8.33	8.33
9	8.33	25.00	16.67	16.67
10	8.33	16.67	33.33	16.67

Hence, the proposed PD model is used for injecting PD pulses in parallel with each section, as well as between winding sections. Further, the DC source is replaced by a signal generator (square function) in order to obtain a PD pulse train. In this way, PD signals were measured across a load resistance with an oscilloscope. Therefore, two data sets are required, one data set for the PD reference signals and the other for the validation process.

The measured PD reference signals for injected PD pulses at sections 1, 2 and 3 are shown in Fig. 8. These signals are similar to the ones in the simulated cases. Fig. 8 also shows the input PD pulse (discharge), which was used for injecting PD pulses in parallel with each winding section, as well as between winding sections. The signals measured in each section including noise can be seen in Fig. 9(a), also measured signals filters using [31] can be seen in Fig. 9(b). The capacitive effect is clearly appreciated due the level of the test transformer. After that, the algorithm is applied following the described process, where the optimal decomposition level is equal to 5. Then, those signals are processed up to the optimal level in order to compute the DWT for each measured signal and to estimate the PD location according to the proposed divergence.

Finally, the algorithm is validated and its results are presented in Table 6. The results for each scale were analyzed and it can be seen that the proposed algorithm produces good results in both cases. However, this is satisfied up to the optimal decomposition level. After that the results are affected, giving accuracy percentages less than 85%.

The comparison between the simulations and measurements performed show that the proposed algorithm has a satisfactory performance in locating PD in parallel along each winding section and between winding sections. Moreover, the results lead to the conclusion that *db*7 gives better results than *db*8 for locating PD signals. Due to the proposed method is based on the optimal decomposition level, to avoid that the results depend of the chosen mother wavelet. In Table 6, the proposed Shannon entropy is validated and the algorithm performance is fitting to PD location up to the optimal decomposition level. Therefore, the results, based on the given algorithm, lead to the conclusion that db7 gives better results than db8 for locating PD signals (see details in Table 6, scale 5).

9. Conclusions

A new algorithm to PD location in transformer windings is proposed that is evaluated with a ladder network of lumped parameters. Also, experimental tests were carried out in a distribution transformer winding to validate the proposed method. PD signals are processed using the DWT and PD location is carried out by means of the KL-modified divergence, which is introduced for locating PD in transformer windings. The obtained results showed that *db*7 gives better results than *db*8 for locating PD in transformer windings with an error percentage less than 5%. The authors conclude that the KL-modified divergence is another alternative that can be applied for PD location in transformer windings, helping to overcome the complexity when the estimation of the PD location is required. Further, its results can be evaluated in the frequency domain. As a future work, the authors propose to analyze multiple discharges along the winding, so as evaluate other PD model in order to represent the physical nature of the PD source.

Acknowledgment

The authors acknowledge the financial support given by CONACYT (Mexico) – CONICET (Argentina) through the bilateral cooperation project 189382.

References

[1] O. Perpi nán, M.A. Sanchez-Urán, F. Álvarez, J. Ortego, F. Garnacho, Signal analysis and feature generation for pattern identification of partial discharges in high-voltage equipment, Electr. Power Syst. Res. 95 (2013) 56–65.
[2] P.L. Lewin, I.O. Golosnoy, R. Mohamed, Locating partial discharge sources in high voltage transformer windings, in: Electrical Insulation Conference (EIC), Annapolis, MD, 2011.
[3] R.S. Bhide, M.S.S. Srinivas, A. Banerjee, R. Somakumar, Analysis of winding inter-turn fault in transformer: a review and transformer models, in: IEEE International Conference on Sustainable Energy Technologies (ICSET), Kandy, Sri Lanka, 2010.
[4] Caio F.C., A.T. Carvalhoa, M.R. Petragliaa, A.C.S. Limaa, A new wavelet selection method for partial discharge denoising, Electr. Power Syst. Res. 125 (2015) 185–195.
[5] M. Majidia, M. Oskuoeeb, Improving pattern recognition accuracy of partial discharges by new data preprocessing methods, Electr. Power Syst. Res. 119 (2015) 100–110.
[6] W.M.F. Al-Masri, M.F. Abdel-Hafez, A.H. El-Hag, A novel bias detection technique for partial discharge localization in oil insulation system, IEEE Trans. Instrum. Meas. 65 (2) (2016) 448–457.
[7] S. Jayalalitha, V. Jayashankar, A correlation method for detection of partial discharges in transformers, IEEE Trans. Power Deliv. 21 (1) (2006) 531–532.
[8] M. Nafar, T. Niknam, A. Gheisari, Using correlation coefficients for locating partial discharge in power transformer, Electr. Power Energy Syst. 33 (2011) 493–499.
[9] V. Jeyabalan, S. Usa, Frequency domain correlation technique for PD location in transformer windings, IEEE Trans. Dielectr. Electr. Insul. 16 (4) (2009) 1160–1167.
[10] M. Homaei, S.M. Moosavian, H.A. Illias, Partial discharge localization in power transformers using neuro-fuzzy technique, IEEE Trans. Power Deliv. 29 (5) (2014) 2066–2076.
[11] Z.D. Wang, S.N. Hettiwatte, P.A. Crossley, A measurements-based discharge location algorithm for plain disc winding power transformers, IEEE Trans. Dielectr. Electr. Insul. 12 (3) (2005) 416–422.
[12] J.M. Abdallah, Power transformer windings partial discharge location by transfer function, Int. J. Electr. Electron. Eng. 4 (6) (2010) 428–433.
[13] A.M. Jafari, A. Akbari, H.R. Mirzaei, M. Kharezi, M. Allahbakhshi, Investigating practical experiments of partial discharge location in transformers using winding modeling, IEEE Trans. Dielectr. Electr. Insul. 15 (4) (2008) 1174–1182.
[14] S.D. Mitchell, J.S. Welsh, R.H. Middleton, B.T. Phung, A narrowband high frequency distributed power transformer model for partial discharge location, in: Australasian Universities Power Engineering Conference (AUPEC), Perth, Australia, 2007.
[15] T.Y. Ji, W.H. Tang, Q.H. Wu, Partial discharge location using a hybrid transformer winding model with morphology-based noise removal, Electr. Power Syst. Res. 101 (2013) 9–16.
[16] G.B. Gharehpetian, H. Mohseni, K. Moller, Hybrid modelling of inhomogeneous transformer winding for very fast transient overvoltage studies, IEEE Trans. Power Deliv. 13 (1) (1998) 157–163.
[17] S. Pramanik, L. Satish, Estimation of series capacitance of a transformer winding based on frequency–response data: an indirect measurement approach, IEEE Trans. Power Deliv. 26 (4) (2011) 2870–2878.
[18] S.N. Hettiwatte, Z. Wang, P.A. Crossley, Estimating transformer parameters for partial discharge location, in: Australasian Universities Power Engineering Conference (AUPEC), September 28–October 1, 2014.
[19] IEC-60270, High-Voltage Test Techniques-Partial Discharges Measurement, 2000.
[20] A. Abu-Siada, N. Hashemnia, S. Islam, Mohammad A.S. Masoum, Understanding power transformer frequency response analysis signatures, IEEE Electr. Insul. Mag. 29 (3) (2013) 48–56.
[21] D. Guillen, G. Idarraga-Ospina, E. Mombello, Partial discharge location in power transformer windings using the wavelet Laplace function, Electr. Power Syst. Res. 111 (2014) 71–77.
[22] S. Okabe, G. Ueta, H. Wada, Partial discharge signal propagation characteristics inside the winding of gas-filled power transformer study using the equivalent circuit of the winding model, IEEE Trans. Dielectr. Electr. Insul. 18 (5) (2011) 1668–1677.
[23] V. Jeyabalan, Future template numerical interpretation techniques for PD pulse location in transformer windings, Electr. Power Syst. Res. 112 (2014) 37–47.
[24] H.W. Dommel, Electro-Magnetic Transient Program, BPA Portland, Oregon, 1986.
[25] Mohammad S. Naderi, T.R. Blackburn, B.T. Phung, Mehdi S. Naderi, A. Nasiri, Application of wavelet analysis to the determination of partial discharge location in multiple-α transformer windings, Electr. Power Syst. Res. 78 (2008) 202–208.
[26] A.M. Gaouda, A. El-Hag, T.K. Abdel-Galil, M.M.A. Salama, R. Bartnikas, On-line detection and measurement of partial discharge signals in a noisy environment, IEEE Trans. Dielectr. Electr. Insul. 15 (4) (2008) 1162–1173.
[27] S. Mallat, A Wavelet Tour of Signal Processing, Academic Press, USA, 1987.
[28] A. Samui, S.R. Samantaray, Wavelet singular entropy-based islanding detection in distributed generation, IEEE Trans. Power Deliv. 28 (1) (2013) 411–418.
[29] M.A. Lexa, Quantization via empirical divergence maximization, IEEE Trans. Signal Process. 60 (12) (2012) 6408–6420.
[30] X. Ma, C. Zhou, I.J. Kemp, Interpretation of wavelet analysis and its application in partial discharge detection, IEEE Trans. Dielectr. Electr. Insul. 9 (3) (2002) 446–457.
[31] J. Li, T. Jiang, S. Grzybowski, C. Cheng, Scale dependent wavelet selection for denoising of partial discharge detection, IEEE Trans. Dielectr. Electr. Insul. 17 (6) (2010) 1705–1714.