Wavelet Analysis and Classification for Partial Discharges

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Abstract: - This paper presents a new method for insulating breakdown detection. The main idea consists in conceiving a general method, adaptable to all sort of insulating material subject to partial discharges (PD) phenomena.

The first step is the analysis of the available recorded experimental PD parameters. The obtained information is correlated with the results of the wavelet transform decomposition method. Subsequently, interpreting the results computed on the experimental data set helps to decide whether and where the method should be employed, and to establish the premises for a further functioning states classification method, which will be used within a decision algorithm.

Key-Words: - wavelet, hierarchical indexed classification, partial discharges (PD), insulation ageing detection.
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1 Introduction

The electric turbogenerator supervision is an expensive and quite rare operation. But in case of failure, the damages are very important. The principal cause of turbogenerators failure is the partial discharges phenomena, which causes the degradation of coils insulation materials. Avoiding the explosion of the turbogenerators means supervising the state of each coil, which implies important costs.

A new method of automatic supervision of the insulation state is proposed in this paper, based on the analysis of the partial discharges phenomena. Disposing of different PD signals features for several coils submitted to quick ageing until breakdown, the analysis of the PD phenomena is used to conceive a general method applicable to several insulation types.

A well-known method that applies to signals without associated model is the wavelet decomposition. The general purpose is to detect the beginning of a very quick degradation of the insulating material by observing the changes produced in the different measured PD characteristics. So the analysis moves from the measured signal to its wavelet transform coefficients.

Like in any failure detection procedure, a particular attention has to be paid to false alarms. This problem is to be taken in charge by a classification method using the obtained indicators of the insulation state.

The paper is organised as follows: the second section presents the general features of the PD signals; the third section contains the wavelet transform approach; the fourth section develops a hierarchical classification method, and the last section presents the results of the entire analysis on the recorded PD signals.

2 Analysed PD signals features

Three so-called "models" of PD phenomena taking place in a capacitor insulating material: the point-surface PD model, the surface-surface PD model and the void (or gas) PD model [4] appear simultaneously while the capacitor is under tension.

On the other side PD tension amplitudes may be significant or small, frequent or scarce. It hasn't been proved that any combination of these properties leads sooner to insulation breakdown. So the general hypothesis is that all PD pulses have an equal contribution to insulation degradation.

The signals to be analysed are: the maximum amplitude, the mean amplitude and the number of PDs. For the accuracy of the analysis, the final breakdown measurements have been excluded.

From a physical point of view, the PDs are supposed to occur in the same opened channels with an increasing transferred electrical charge. But the analysis of the measured signals autocorrelation during the normal functioning reveals that the coefficients are weak and slightly increasing in the ageing period, so they could not be used for further analysis of the phenomena.

Another step was the analysis of the signals spectral properties. All signals have an equal distribution of spectral lines – the same as a white noise – superposed on a low frequency spectrum line of which neither the dimension nor the frequency changes in time.

For some PD characteristics, in the end of the signals sequence, a new group of high frequency spectral lines appears, but it's more than probable this behaviour won't repeat for other PD signals.

These anticipated considerations over the available PD signals imply that a more general method of analysis should be employed.

3 Wavelet transform approach

The wavelet transform is a remarkably powerful and general method used to detect singular behaviours in any sort of signal. Generally it brings out information where other classical methods have failed.

Theoretically applying the wavelet transform to a signal is equivalent to applying numerical filters. But the difference between the time-frequency Fourier transform and the time-scale wavelet transform is that in the second one the multiresolution analysis allows several projections of the signal on overlapped function subspaces [1].

For the signal $f(t)$, the scaling function generating the multiresolution basis is expressed as:

$$\varphi_{j,n}(x) = 2^{-j/2}\,\varphi(2^{-j}t - n), \quad (1)$$

where φ is the mother wavelet function, j indicates the level of decomposition and n is the time translation factor. Here the scaling factor is chosen 2 as further the analysis places itself into the dyadic case.

The **approximation** coefficients give the low-pass smoothed information over the signal, the breaks being progressively attenuated. The **detail** coefficients contain the information on the signal skeleton discontinuities [2]. These wavelet coefficients are computed according to the following tree decomposition algorithm:

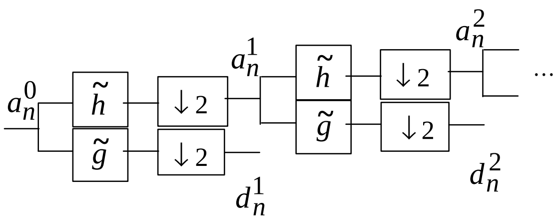

Fig.1 Wavelet decomposition tree. $\tilde{h}$, $\tilde{g}$ - decomposition filters for approximations, respectively details; $\downarrow 2$ - downsampling with factor 2.

Consequently, the level j wavelet decomposition coefficients are computed recursively using the relations:

$$a_n^j = \sum_l \tilde{h}_{2n-l}\, a_l^{j-1} \quad (2)$$

$$d_n^j = \sum_l \tilde{g}_{2n-l}\, a_l^{j-1} \quad (3)$$

As an example, the numerical filters associated with the wavelet decomposition using Haar mother wavelet are:

$$\tilde{h}_n = \left\{\ldots, 1/\sqrt{2}\Big|_{n=-1}, 1/\sqrt{2}\Big|_{n=0}, \ldots\right\} \quad (4)$$

$$\tilde{g}_n = \left\{\ldots, -1/\sqrt{2}\Big|_{n=-1}, 1/\sqrt{2}\Big|_{n=0}, \ldots\right\} \quad (5)$$

Graphically the difference between the time-frequency Fourier transform and the multiresolution analysis wavelet transform may be represented as:

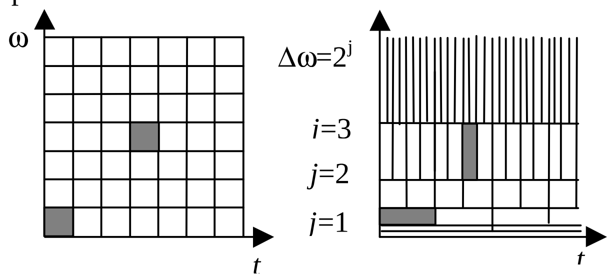

Fig.2 Comparison between the time-frequency (left) and the time-scale (right) plan paving.

The dyadic grid detection principle consists in finding temporal coincidence of significant wavelet decomposition coefficients through several levels. This idea is ilustrated by the positionning of an event in a knot of the grid. Otherwise the energy of the event is shared among all vertical neighbour coefficients.

One remark is necessar: the wavelet transform doesn't bring any additional information on the analysed signal. The growth of the representing space, implying a redundancy, only brings to the fore particular behaviours of the signal.

The wavelet transform is "blind" regarding the gentle segments of a signal (which might be modelised by a polynomial function) as its weak coefficients are considered zero.

As mentioned in the previous section, the PD measurement signals have properties close to those of a white noise, but also a pertinent low-frequency spectrum line.

In parallel, during the ageing process new groups of high energy spectral lines might appear in the high-frequency domain, so it would be interesting to decompose the experimental signals through wavelet transform also in the subspaces associated with details.

The main disadvantage of multiresolution analysis is that only the decomposition of low-frequency domain is allowed, but it's forbidden to decompose in the same way the high-frequency domain. More precisely, approximation and detail coefficients for the next decomposition level may be computed only from the actual approximation coefficients not from detail coefficients.

The solution to this inconvenient is to apply wavelet package transform which has been developed for allowing the access to all decomposition coefficients corresponding to equal cut out of the frequency domain for every level.

The tree decomposition represents clearly the mechanism of wavelet package transform:

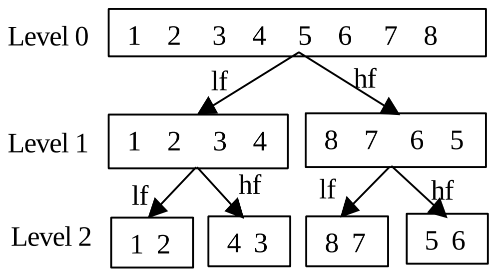

Fig.3 Wavelet package decomposition tree.

The numerals represent the indices of the naturally ordered frequencies. It has to be mentioned that computing the detail coefficients implies reversing the order of the indices for the high-frequency domain.

Analysing the PD signals with the wavelet package could help us to detect the appearance and the shifting of high-energy frequency groups.

4 Hierarchical classification for insulation ageing detection

In order to avoid coefficients thresholding, which is not very suitable to PD signals, is proposed a classification of the computed wavelet coefficients into classes associated with the three states of an insulation when put under tension - starting "clst", normal functioning "clfn", and ageing "clal".

The most appropriate method seemed to be the hierarchical indexed classification [5].

H_E is a **hierarchy** over the set E if H_E is a set of partitions of E so that:

$$\varnothing \subset H_E,\ E \subset H_E, \qquad (6)$$

and

$$A \in H_E, B \in H_E \Rightarrow \begin{cases} A \cap B = \varnothing \\ \text{or } A \subset B \\ \text{or } B \subset A \end{cases}$$

The application $d^* : H_E \to \text{IR ou } [0,1]$ is **index** over H_E if it verifies:

$$\forall A \in H_E, \forall B \in H_E, A \subset B \Rightarrow d^*(A) \le d^*(B) \qquad (7)$$

If $d^*(A) >>$ then A is heterogeneous.

The indexed hierarchy may be represented by an aggregation tree, whose leafs are the elements of the set E displayed on the horizontal axe and knots have indices height (representing the energy spent for the aggregation).

A **cut** of the hierarchical tree is the choice of the resulting classes according to all aggregation indices.

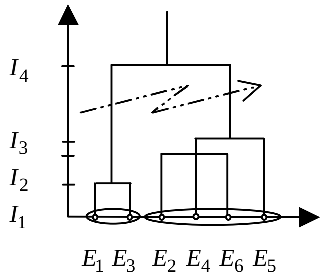

Fig.4 Hierarchical indexed classification tree; the flash represents the cut used to obtained the two encircled classes.

The algorithm is very simple and adaptable to any sort of distribution of the set E.

1.	Introduction of data. Every element of E is a class.
2.	1. Creating a table of distances between classes. 2. Searching the smallest distance. 3. Coupling the nearest classes. 4. Return to 2.1. until there is only one class left.

Table 1. Hierarchical classification algorithm.

The distance between classes is computed according to previous established rules, such as maximum jump, minimum jump, mean jump or variance criterion.

For example, the expression of the maximum jump between the classes A and B is:

$$\tilde{d}(A, B) = \max_{\substack{x \in A \\ y \in B}} d(x, y) \qquad (8)$$

The minimum jump criterion is to be used carefully since it is sensitive to chains of elements between classes. The best criterion, but also the most expensive from the floating-point operations number point of view, is the variance criterion.

Cutting the hierarchical tree where the energy requested for aggregation is maximal (during the entire procedure) generates the best classification.

This method is suitable for a further decision algorithm taking into account the classification and the evolution of the classes in time as the general purpose is to implement an on-line detection algorithm.

5 Analysis of PD signals

Three measurement files contain the recorded PD parameters during an ageing laboratory cell experiment (measures of partial discharges in the insulating materials of three different coils) beginning when insulation has been put under tension and ending at its breakdown. For example, "maxampl" is the maximum amplitude of the PD signal recorded for a quick ageing submitted coil:

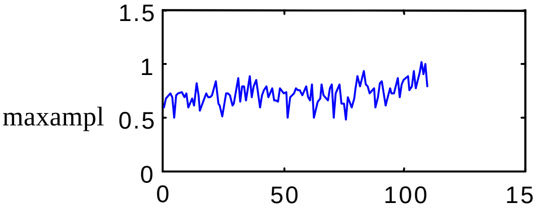

Fig.5 Maximal amplitude of partial discharges in a quick ageing submitted insulating material.

5.1 Spectral analysis of experimental data

The time wideness of the weighting window determines its pass-band. If the window is wide, its pass-band is narrow and vice versa.

Theoretically a narrow pass-band window brings out the pure frequencies in the analysed signal, and a wide pass-band window brings out the noise spectrum. The confidence interval of the power spectral density computed values is evidently much smaller in the first case.

Performing the wide pass-band window spectral analysis on our experimental signals brings to the fore a strong resemblance between their properties and a white noise spectral properties, which means an equal power distribution for all frequencies.

Meanwhile the narrow pass-band window spectral analysis revealed the presence of a low frequency spectral line whose power is not much higher than other frequencies power, but is more accurately calculated.

The same analysis performed on-line on all PD parameters (using a fixed length time sliding window) established that the low-frequency spectral line doesn't change (neither its power, nor its frequency) during insulation ageing, but in some parameters cases groups of high frequency spectral lines may appear.

For the "maxampl" signal the narrow and the wide pass-band windows are obtained using the Matlab5.0 function "hanning" over the whole time length of the signal, respectively only over 10 time samples.

The figures below show the frequency contents evolution. The bold curves are the computed power spectral densities, and the dotted curves delimit the confidence interval.

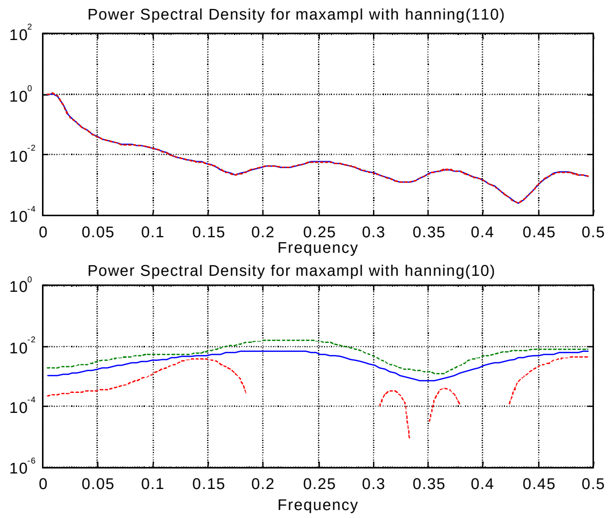

Fig.6 States of starting and normal functioning.

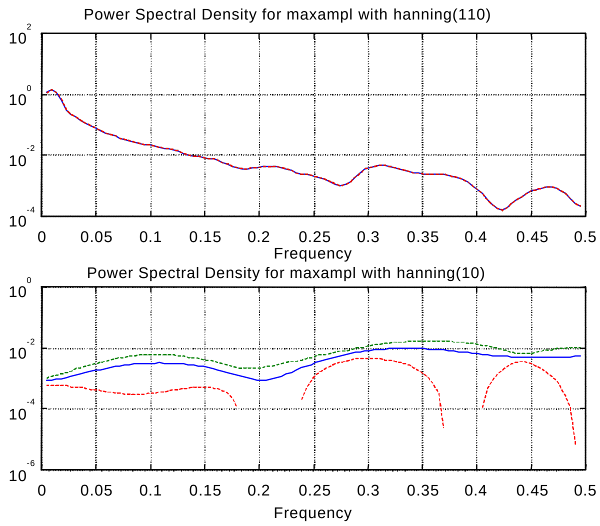

Fig.7 Ageing phase.

The high frequency behaviour isn't the same for all PD parameters of one insulation type, which could be comprehensible as different parameters don't contain the same information [3]. Even more, this behaviour is not confirmed for the same PD parameter from one insulation to another. This is the main reason why the PD influence in the insulation ageing process is not to be found in the PD signals spectral properties.

5.2 Wavelet decomposition

While comparing the wavelet decomposition of the PD parameters signals with classical predefined scaling functions like Haar, Daubechies, biorthogonale, etc, the Haar wavelet presents the same performances as Daubechies1 and Bior1.1. A comparison between these wavelet transforms is presented in the Table 2.

		Insulation		
		maxampl	meanampl	number
Haar	Alarm	74%	71%	85%
Db1	Alarm	74%	71%	85%
Bior1.1	Alarm	74%	71%	85%
Bior1.3	Starting	0–20%	0–20%	0–20%
	Normal Funct.	20–78%	20–78%	20–78%
	Alarm	78%	78%	78%

Table 2. Detecting ageing phase with wavelet decomposition.

The wavelet Bior1.3 is more appropriate to separate the different functioning states of the insulation, but is less rapid in alarm trigging.

The third level Haar wavelet multiresolution decomposition coefficients (2), (3) are represented in the figure below:

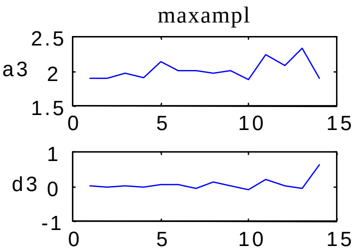

Fig.8 Haar wavelet multiresolution decomposition coefficients - level 3.

Visually, the behaviour of the wavelet coefficients changes in the ageing phase, but it is not very obvious that a simple thresholding would be an enough precise strategy for alarm trigging.

5.3 Wavelet coefficients classification

The hierarchical indexed method uses the maximum jump criterion (8) in computing the distances between classes.

Applying the algorithm to the wavelet coefficients presented in the previous subsection leads to the classification presented in Table 3.

The class of important coefficients "clal" is well separated from the class of weaker and medium ones, but the alarm is trigged too late. The risk of uncertain instant alarm was not eliminated.

A more relaxed classification (cutting the arborescence one iteration earlier) leads to a class "clal" containing several coefficients, which are not successive in time. So the classification should be modified as to include in the alarm class all the in-between instants.

Another solution could be relaxing the cut of the hierarchical tree by associating probabilities of alarm to each element of a class [6]. This new problem remains to be taken in charge by a future decision algorithm.

Approximation coefficients			Detail coefficients		
clst	clfn	clal	clst	clfn	clal
1.895 1.903 1.904 1.918 1.871 1.970 1.973 2.013 2.013 2.008	2.140 2.092 2.227	2.334	0.002 0.003 0.012 -0.008 0.021 -0.022 0.066 0.070 0.129 -0.068 -0.077 -0.052	0.191	0.639

Table 3. Classification of wavelet coefficients.

6 Conclusion

The paper presents an application of the wavelet decomposition method in early detecting the breakdown of insulating materials caused by the partial discharges phenomena.

At the first step are obtained the coefficients of the wavelet decomposition containing all the information about several PD signals behaviour, which are used in a second step to classify the state of the insulation into three classes: starting, normal functioning and ageing. At the beginning of the insulation ageing process is trigged the alarm for an imminent breakdown.

In prospect the decision method has to be elaborated, also having in view the implementation of all algorithms on-line.

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