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MONITORING TRANSIENT PHENOMENA IN POWER NETWORKS: THE KEYPOINT OF ENERGETIC DISTRIBUTION SECURITY

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Rezumat. *Semnalele tranzitorii generate de sistemele electrice au origini diferite și pot fi considerate ca fiind normale sau deficiente. Monitorizarea și analiza lor este crucială atunci când fenomenele generate de acestea pot duce la distrugerea totală sau parțială a sistemului. Datorită aparițiilor scurte ale acestora, analiza semnalelor tranzitorii este o provocare în domeniul procesării semnalelor. În această lucrare sunt prezentate mai întâi diferite metode operaționale de analiză a semnalelor tranzitorii generate de sistemele electrice. Sunt investigate și testate pe date reale câteva clase pentru analiza semnalelor tranzitorii. Experimentele prezentate au fost realizate în colaborare cu departamentul de cercetare dezvoltare din cadrul EDF (Electricité de France) în perioada 2007-2009.*

Abstract. *Transient signals generated in electrical systems are different origins and they could be considered as normal or as default. Their monitoring and analysis is crucial while the phenomena behind them could lead to a partial or total destruction of the system. Because of their brief occurrence, the transient signal analysis is a challenging field in signal processing domain. In this paper, we illustrate firstly the different operational methods to deal with the transient signals issued from electrical systems. Some classes for transient signal analysis are investigated and tested on real data. The experiments presented have been done in collaboration of EDF (Electricité de France) R&D department in the period 2007-2009.*

Keywords: transient signals, wavelet transform, energy distribution system, partial discharge, signal's distribution

1. Transient phenomena in power networks

Transient signals generated by electrical systems (in production, transport, distribution and consumption) have different origins and can be considered normal or materializing a fault. Such is the case of partial discharges (PDs) which are among the most frequent causes of breakdown in the electrical systems because, according to [IEC2000], 30% of the breakdowns in the electrical systems are due to the defaults in isolation. The partial discharges can appear in the entire production-transport-distribution channel, as illustrated on several examples in the figure 1, and can be caused by the material's wear and fatigue, humidity, manufacturing problems, etc.

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The high rate of the breakdowns caused by the PDs, as well as the complex problem connected to the characterization of the PDs is reasons to give a special attention to this type of transient phenomena. This section is aimed to point out on the different existing techniques for transient signal detection, motivating also the interest for further development signal analysis tools that will solve the problems of current methods.

The phenomena generating PDs have been studied intensively; the first studies dating back form the 1930s. In [Krivda95], the author proposes a state of the art class of methods used in the PD recognition. In spite of the different techniques employed for the detection of PDs (which we will mention briefly in this paragraph), they rely on the effects of the physical phenomena which causes the transient phenomena. Thus, the partial discharges are generated by the defaults in the isolation which evolve [Krivda95] in an unpredictable manner (we do not know when will the breakdown occur in the system) in time. Generally, the PDs are emerging by the apparition of very short transient signals covering a large spectral band as well as an optical signature. There are the effects on which the existing techniques of detection-localizations-characterizations of PDs rely upon.

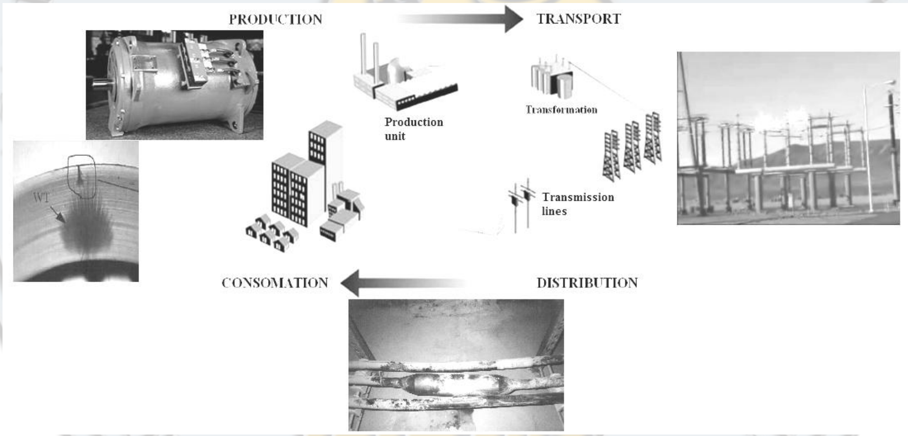

Fig. 1. Occurrence of the partial discharges in electrical systems.

A. Chemical detection

This technique uses the chemical effect of the PDs which, under the action of the electrical field, consists in modifying the chemical structure of the zone of material subject to PDs. In order to highlight the presence of PD phenomena, one must gather a sample and analyze it. This type of technique is used to study the PDs in high voltage transformers (which contain oil) where the presence of gases like hydrogen, methane, carbon dioxide (DGA technique – dissolved gas analysis) or glucose derived products on the sides of the transformer can indicate the existence of the faults responsible for the PDs [Kemp95]. This detection technique has several important limitations. The first is that it does not allow localizing the

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source of the PDs. Finally, this method can be applied to a reduced number of cases and, more precisely, when the chemical changes will make a pertinent indication (this is not the case of cables or electrical systems where the isolation is air, for example).

B. Electrical detection-localisation-characterisation

This technique, largely used [Hikita *et all* 90], [Boggs90], consists in acquiring the electrical signal present in the system and detecting the existence of short impulses (by the order of nanoseconds) generated by all transient electric phenomena. The distribution of these impulses can indicate at the same time the presence of transient sources, as well as their nature (measuring their position with respect of the network's frequency – 50 or 60 Hz). In figure 2 an example is illustrated and we can notice the presence of impulse distributions with respect of the 50 Hz sinusoid.

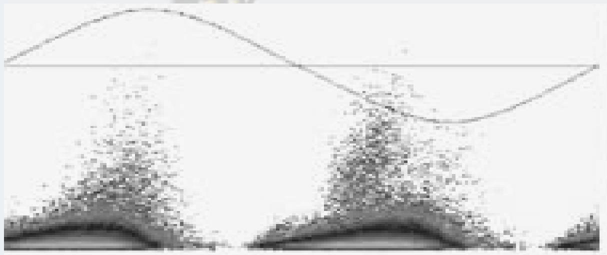

Fig. 2. PDs detection-localization diagram based on electrical signals.

The basic diagram employed by this measuring technique is illustrated in figure 2. The sensors are placed on the terminal of the surveillance equipment. The main steps of signal processing are the signal acquisition, noise suppression, impulse detection and estimation of their parameters (duration and distribution with respect of the 50 Hz fundamental frequency).

The main limitation of this class of techniques is the presence of narrow band noise, as well as large band noise generated by the coupling elements with the studied equipment. Numerous analysis methods were proposed, based essentially on high order statistics [Kreuger94] and wavelets techniques [Wang *and all* 104], these works concentrated mostly on the detection of PDs as well as the suppression of noise in signals. In order to reduce the level of perturbations one can use the noise subtraction technique, but this technique involves the uncoupling and the *off line* analysis of the system. Actually, once the system is uncoupled, it is possible to record only the noise itself in order to have a perturbation model. It will be possible afterwards to employ the tools for optimal filtering.

Another limitation is the difficulty in terms of material and information processing implied by a global control of a system because a large number of sensors have to be deployed and controlled.

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C. Detection-localization-characterization by electro-magnetic field measurement

This technique, possible due to the latest advances in terms of acquisition of high signal frequencies (sampling frequency around 1GHz), allows the monitoring of transient phenomena without a direct connection with the equipment's terminals (often very difficult to realize in the case of cables). The transitory signal leads to the production of a magnetic impulse which is acquired immediately by a ring placed outside the equipment. The electrical signal from this sensor is digitized and processed in order to detect the presence of the PD. The localization is done by comparing signals issued by several sensors placed on the equipment, as shown in figure 3, where we describe the system designed by Hydro Quebec [Leonard07] and devoted to the surveillance of underground cables.

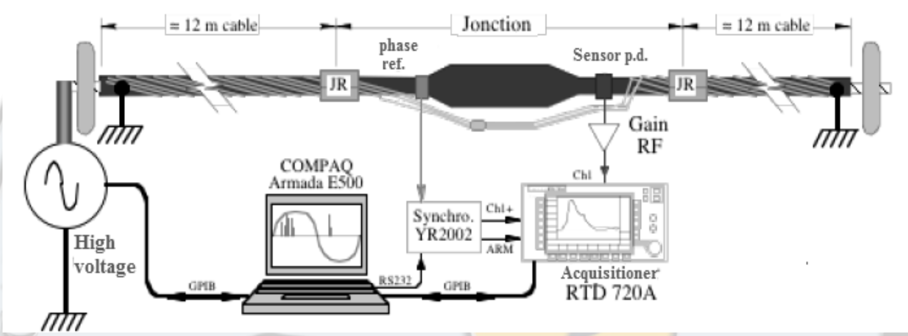

Fig. 3. PDs analysis system based on electromagnetic emission (curtosy of Hydro Québéc, Montréal-Canada).

The current problems in term of signal processing rely essentially on the perturbations generated by the external magnetic field, as well as the multiple reflections producing false transient signals (false alarms). Thus, a current research direction consists in modeling the transfer function of the cable in order to have a model of this type of perturbation and reducing its effect [Leonard07]. Taking into account the instantaneous phase of the pulses is a promising solution as illustrated in [IoanaLeonard06].

In operational terms this is a costly technique because, taking into account the frequency band of interest (superior to 350 MHz), complex acquisition systems are needed which limit the large scale deployment. This prevents the system's global monitoring, but this technique is very efficient for a focused control of a part of system.

D. Detection-localization-characterization by acoustic emission measurements

This class of techniques consists in measuring and exploiting the acoustic signals generated during the PDs. These acoustic signals are generated by the micro explosions which follow the PDs, this phenomena being similar to the apparition of thunders after a lightning [Lundagaard92]. Despite of the complexity of the

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acoustic propagation model (translated in obstacles, reflected trajectories, absorption, dispersion, crossing of heterogeneous environments – air-solid, liquid-solid, etc), the acoustic signature is present in all the points of the system (even if the level of the signal is more or less reduced). This remark makes the acoustic measure one of the techniques which can provide an on-line global control (3D) of equipment. However, the efficient use of the acoustic signature, in order to detect, localize and characterize the PDs, is essentially a signal processing problematic, currently open, because of the complex acoustic propagation model, as well as the existing perturbations in the acoustic spectrum (especially the transitory sources like switches, vibrations, pulse noise.

Another advantage of the acoustic techniques is the localization capacity for the sources of PDs using a network of sensors. The localization will be possible, if the problems of propagation and separation of PDs signals from artifacts (noise, transient sources) are correctly solved. This is true only for a reduced number of situation and when the propagation is simple. The most known example is the monitoring of high power transformers and whose PDs control uses successfully acoustic sensor networks [Eeftherion95]. The detection-localization techniques have the advantage of a reduced level of perturbations as well as a simple propagation environment without obstacles and/or additional transient sources. The propagation context is clearly more complex in the case of tuning machine, for example.

This section presented few methodologies for monitoring electrical phenomena. We saw that they exploit the physical behavior of such phenomena but the signal analysis techniques are the key point for the efficiency of such method. For these, reason, we focus, in the next section, on the potential signal processing techniques that will be aimed to ensure and to improve the efficiency of current systems.

2. Analysis of transient phenomena - methods and experimental systems

The main signal processing purpose concerning the transient signals of electric origin is to detect and localize their source enabling also the prevention, diagnostic and control of the breakdowns. One of the problems concerning the transient signals is that they are defined within a reduced number of samples and are difficult to model. Consequently, the characterization of such signals is currently a challenge of increasing interest. As it was previous explained, the parameters of the electrical transients are closely connected to the physics of the phenomena being at their origin. Being capable to characterize these transients and their parameters allows to their classification by type of events.

In the last twenty years, the signal processing tools as High Order Statistics (HOS), the wavelets transform and the spectrogram are largely used to realize the detection and localization of the transients. The HOS method is adapted for the

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detection of transients embedded into a white additive Gaussian noise [Rav97]. This method gives high HOS values for the entire non Gaussian component such as transient, whereas all of the Gaussian part of the signal gives HOS values very close to zero (quasi-nulls). The wavelet and spectrogram coefficients are also based on the energy criteria.

Recently, a new time-frequency concept was introduced in signal processing, based on the moments of complex lag [Stankovic-Cornu-Ioana-07]. This distribution offers the possibility of representing time-frequency components which are very nonlinear, with considerably greatly reduced interference terms. Contrary to HOS, wavelets and spectrogram, this concept of "complex time distribution" concentrates, based on the signal's samples, directly on the signal's instantaneous phase information without taking into account the signal's amplitude and variations. Consequently, for detection of transients with strong amplitude variations, a method of phase analysis proves its interest.

This section will briefly describe these signal processing concepts and the application to electrical transients will be defined. The signals used in this were obtained with the help of the experimental framework provided by the EDF R&D, Paris. The following scenario has been defined in order to get realistic transient data. A signal is emitted at one extremity of the cable and, during its propagation, when a fault takes place at one point in the cable; a part of the emitted signal's amplitude is reflected starting from that point on due to the impedance discontinuity caused by that fault.

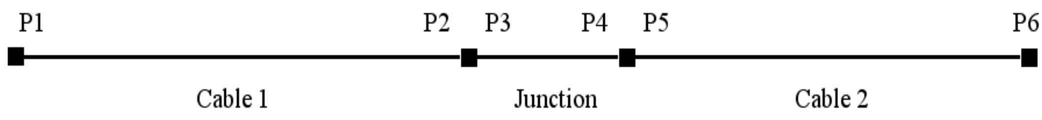

Fig. 4. Configuration diagram of two cables separated by a junction.

The cable network corresponds here to two cables of different characteristics (or not), separated by a junction (figure 4). During its propagation in the "cable – junction – cable" line, the pulse is reflected at the "cable/junction" interface point, at the fault points and at the end of the cable point. As illustrated in figure 5, the analyzed signal is composed of the original emitted pulse and pulses issued by various reflections, thus affected by lags, amplitude attenuations and phase differences.

2.1. Spectrogram

In order to overcome the limitations of the Fourier transform (FT) in the context of non-stationary signals, one can consider the signal as having local stationarity in an analyzing window of appropriate lengths. We construct the Fourier analysis

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of the signal's portions weighted with an appropriate length time window *h* (Hamming par example, figure 6). This principle is equivalent to approximating the signal with a set of elementary functions which are localized simultaneously in time and frequency [Coh95, p. 53].

$$STFT_x^{(h)}(t,f)=\int x(\theta)h_{t,f}^{*}(\theta)\,d\theta=\int x(\theta)h^{*}(\theta-t)e^{-2\pi jf\theta}d\theta \tag{1}$$

This relation represents the scalar product between the signal $x(t)$ and the basis functions $h_{t,f} = h(\theta - t)e^{j2\pi f\theta}$. The representation given by the relation (1) is called ***Short Time Fourier Transform – STFT***.

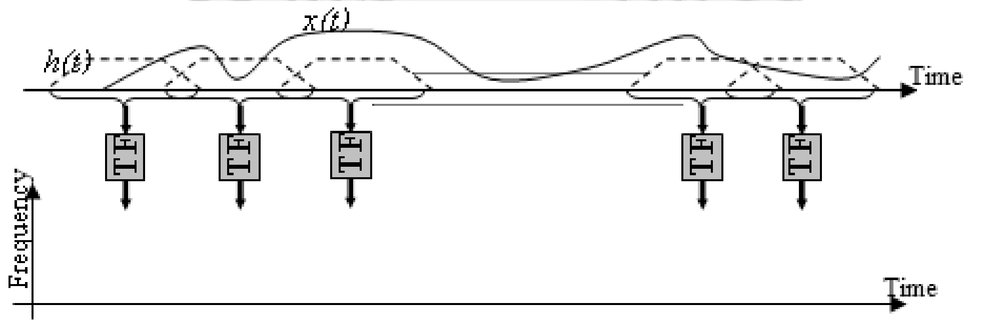

Fig. 6. Local spectrum interpretation for the Short Time Fourier Transform

According to its definition, the STFT has complex values. Practically only the squared modulus is represented in general, as shown here. The transformation realized is called the ***spectrogram*** [Coh95].

The STFT or the spectrogram considers a non-stationary signal as a succession of quasi-stationary situations, scaled to the weighting window *h(u)*. Despite its simplicity and properties, the STFT and the spectrogram are limited by the uncertainty principle of Heisenberg [Coh95] concerning the trade-off between the time and frequency resolutions Δt and Δf. These two terms are *antagonist*, being subject to a compromise between the temporal and frequently resolutions. In general:

- For a transient signal a good temporal resolution is required, which demands a short window, thus limiting the frequency resolution;
- Otherwise, if a fine frequency analysis is needed, a long window has to be used, which has the double effect of averaging the frequency contributions on the duration of the window and reducing the temporal resolution.

Description of the detection method

The spectrogram-based detection method consists simply in commuting and representing the spectrogram distribution of the analyzed signal. The temporal

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detection curve will be the curve (1 dimensional) of values greater than a threshold of the columns of the obtained distribution:

$$CD_{SPEC}(t) = \left\{ \sum_f |STFT(t,f)|^2 \geq \beta \right\} \tag{2}$$

where $\sum_f |STFT(t,f)|^2$ represents the spectrogram's time marginal distribution and β – the detection threshold. The transient are generally characterized by pulses with a good localization in time having large spectral content distributed around the temporal centre of the impulses. Remembering this remark, the detection curve is obtained by comparing the temporal marginal distribution with a detection threshold. The next figure shows the detection curve of a signal generated by the scenario illustrated in the figure 5.

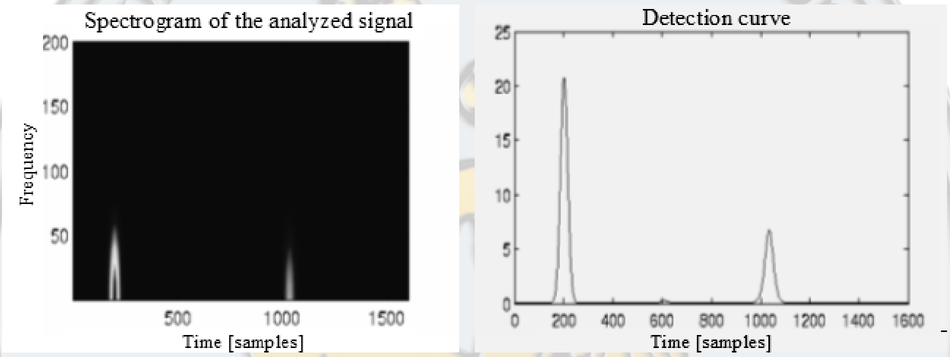

Fig. 7. Spectrogram of a PD signal and the detection curve.

In the context of spectrogram-based detector, the choice of the threshold presents major difficulties. In general, there is no universal criterion for choosing this threshold and is always the subject of a compromise between a good detection and the rate of false alarms. In addition, the time-frequency analysis based on short time Fourier transform is not, generally, an appropriate tool for the analysis of transient signals. Thus, the interest for wavelet analyses increased since 90's.

2.2. High Order Statistics (HOS) and wavelets

The wavelet transform (WT) is the traditional tool for the representation of transient signals. The Discrete Wavelets Transform (DWT) decomposes a signal into a wavelet base starting from a reference wavelet, *φ(t)*, called "mother wavelet". This basis of wavelets can be represented as a tilling of the Time-Scale plane knowing that the Scale parameter is just the inverse of the Frequency parameter.
Each block of this tilling represents a series of wavelets and corresponds to the mother wavelet modified by a lag *u* and by a scale factor *a*, i.e. $\varphi\left(\frac{t-u}{a}\right)$.

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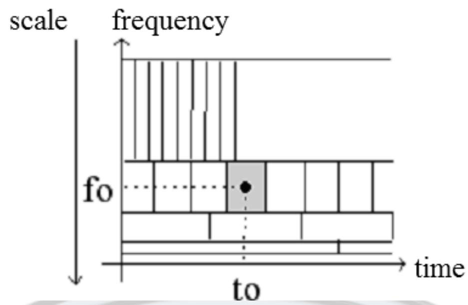

Fig. 8. Time-frequency tilling specific for wavelets.

The representation provided by the DWT contains more or less strong wavelet coefficients which are the projections of the signal on each basis wavelet function. The DWT shows its efficiency to detect the transients as a consequence of the similarity between the wavelets (in their shape and nature) and the transient signals. Consequently, the distribution obtained by DWT gives high values for the scalar products between the used wavelet and the signal's transient component.

In 1996 Ravier proposed, for the transient detection and localization, a method which combines the advantages of both HOS and the wavelet theory. This methodology relies on the non-parametric approach stating that the transients are characterized by statistic properties which are in contrast with those of the noise. The underlying idea from Ravier's work is considering that, in the case of a signal embedded in a white Gaussian noise, the signal's components distinguish themselves from the noise by their HOS properties [Men91]. In order to detect them, one must try to highlight the zones where the signal presents changes connected to these statistic properties. Considering the signal as being segmented in time frames, the idea a fine **segmentation** when the signal changes its nature and regrouping these segments where the statistic properties of vary slightly [Rav96]. Thus, the segmentation decision can be expressed as a test of binary hypotheses:

$$\begin{cases} H_0\text{: merging - if the segments have the same statistic nature;} \\ H_1\text{: keep theme separate if the nature of the segments is different.} \end{cases}$$

In [Rav96], Ravier shows that the non-gaussianity of the majority of a signal's time-frequency components observed in the frequency domain can be "visible" in the space of the wavelet coefficients (a Gaussian signal generates wavelet coefficients C_{jk} which follow a Gaussian distribution and a non-gaussian signal generates coefficients which follow a non-gaussian distribution). Non-gaussian wavelet coefficients are translated into kurtosis values which are different from zero, whereas the Gaussian signals have zero kurtosis up to the 4th order.

Consequently, the use of the kurtosis is well adapted to characterize the difference between noise and transient signals by a test of gaussianity. The decision criterion

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to obtain the best wavelet functions combination is based on the value of an estimator for the kurtosis starting from the wavelet coefficients (according to the figure below). This principle was used by Ravier [Rav95] to extract the best Malvar wavelets decomposition basis.

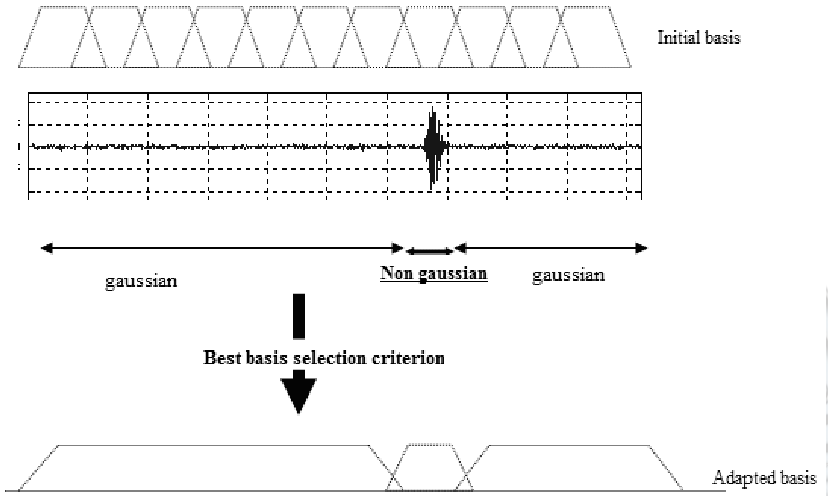

Fig. 9. Segmentation principle to obtain the best basis.

Using these notions, the best basis construction is done by testing the H_0 and H_1 hypotheses as shown:

- for two adjacent segments I_k and I_{k+1} the following conditions are tested:

$$\begin{array}{ll} H_0: & \text{if } kurt(I_j) \le \mu_s \,\&\, kurt(I_{j+1}) \le \mu_s \Rightarrow I_j^{'} = I_j \cup I_{j+1} \\ & \Rightarrow \mathrm{kurt}(\mathrm{I}_j^{'}) = \max\left[kurt(I_j), kurt(I_{j+1})\right] \\ H_1: & \text{if } kurt(I_j) > \mu_s \text{ or } kurt(I_{j+1}) > \mu_s \Rightarrow \text{the intervals will be conserved} \end{array} \tag{3}$$

where $\mu_s = \frac{1}{\sqrt{1-\alpha}}\sqrt{2^s \frac{24}{N}}$ is the computed threshold for each scale s (N is the number of signal samples).

The interval I_j is defined by the wavelet coefficients obtained for the scale s and in the temporal domain $[j\text{-}N/2^s; j+N/2^s]$:

$$I_j = \left\{ C_{\Theta,s} \middle| C_{\Theta,s} = \left\langle x, \psi_{\Theta,s} \right\rangle, \Theta = \left[j - \frac{N}{2^s}, j + \frac{N}{2^s} \right] \right\} \tag{4}$$

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The hypothesis H_0 states that there is no useful signal in the considered intervals and they will merge.

Inversely, the hypothesis H_1 states that an interval or even two can contain useful information and their current state is preserved. The algorithm follows until no other segment can be merged.

The detection curve will be defined by the series of intervals I_j preserved following the algorithm (3):

$$CD_{TOD\_SOS}(t) = \left\{ I_j \middle| I_j \text{ issu de } \mathrm{H}_1 \right\} \tag{5}$$

This detection method provides, for the signal type described in the figure 5 and for an SNR of 30 dB and -8 dB, the following results (see figure 10).

The detection curve corresponds to the kurtosis variation, computed on each time segment, which gives the optimal basis from Malvar wavelets, in terms of Gaussian or non-gaussian components.

The theoretical advantage of this technique, compared to the spectrogram, is the automatic computation of the detection threshold which is done for each scale. Thus, if the chosen wavelet function is adequate, this method is potentially optimal. However, if the signal is composed of transients with different amplitudes (such is the case in figure 5), the method does not detect the low amplitude transients (see figure 10). For this reason, the authors oriented themselves toward detection techniques based on distributions which try to provide an estimation of the instantaneous phase of the signal. Thus, the detection of transients having different amplitudes might be possible.

2.3. Complex Time Distribution

The concept of time-frequency distribution based on complex arguments (Complex Time Distribution – CTD) was introduced by [Stankovic02] as a tool to reduce the inferences by comparison to the Wigner Ville distribution.

A generalization of the CTD concept was defined in [Stankovic-Cornu-Ioana-07] in 2005 – 2007. The starting point of this generalization is the Cauchy integration formula. The use of this theorem makes possible the implementation of the K^{th} order derivative of the instantaneous phase of a signal, $\phi(t)$, as presented below:

$$\phi^{(K)}(t) = \frac{K!}{2\pi j} \oint_{\gamma} \frac{\phi(z)}{(z-t)^{K+1}} dz \tag{6}$$

This expression shows the interest of the complex time: the K^{th} order derivative of the phase function ϕ at time t can be implemented as the complex integral over

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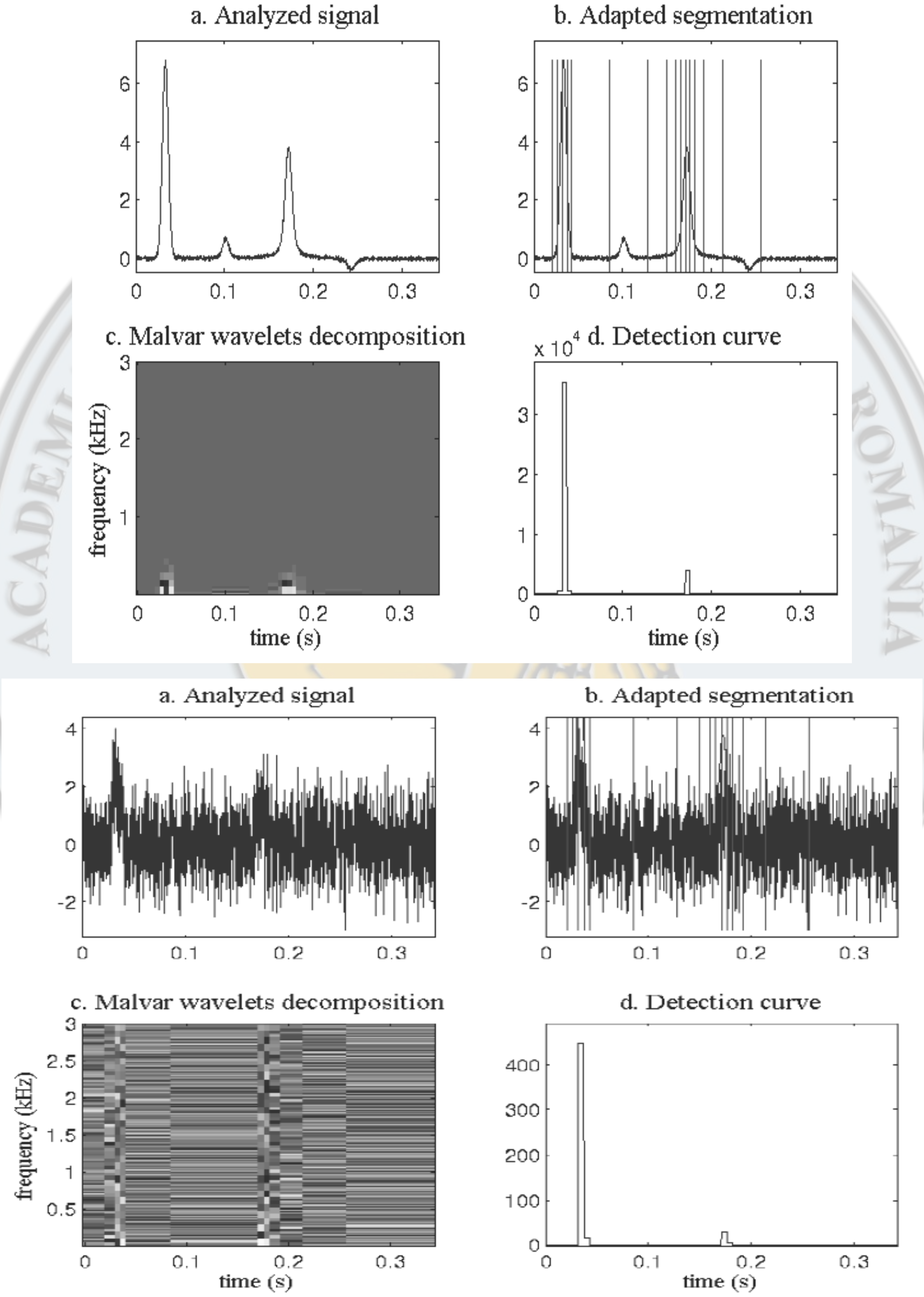
the defined integration contour *γ*, in the complex plane, around this point. This result, coming from the complex function theory, can be interesting, particularly in the study of the derivatives of transient signals, such as electric transients, characterized generally by their fast phase variation.



Case 1: SNR = 30 dB **Case 2: SNR = -8 dB.**

Fig. 10. Detection of transient signals using HOS and wavelets.

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By applying Cauchy's integration theorem and considering as contour a circle of center t, we obtain:

$$\phi^{(K)}(t) = \frac{K!}{2\pi\tau^K}\int_0^{2\pi}\phi(t+\tau e^{j\theta})e^{-jK\theta}d\theta \tag{7}$$

As illustrated by figure 11, the discrete version of such an equation is defined for $\theta = 2\pi p/N$ and $p = 0,\ldots,N-1$, where N is the number of the discrete points.

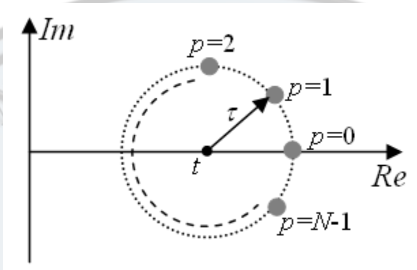

Fig. 11. Definition of comple-time lags.

Starting with these coordinates, the equation (7) becomes:

$$\phi^{(K)}(t) = \frac{K!}{N\tau^K}\sum_{p=0}^{N-1}\phi(t+\tau e^{j\frac{2\pi p}{N}})e^{-j\frac{2\pi pK}{N}} + \varepsilon \tag{8}$$

where ε represents the sampling error.

This approach allows arriving at the expression of the "Generalized Complex Moment" (GCM) and it is expressed as:

$$GCM_N^K[s](t) = \prod_{p=0}^{N-1} s^{\omega_{N,p}^{N-K}}\left(t+\omega Np\sqrt[K]{\tau\frac{K!}{N}}\right) = e^{j\phi^K(t)\tau + jQ(t,\tau)} \tag{9}$$

The GCM is nothing else than a product of terms corresponding to an analyzed signal affected by a complex exponential and a complex lag argument. The implementation of the GCM consists in the evaluation of the samples of the signals at complex instances if time. This evaluation is allowed by means of **analytical extension** of the signal, defied as:

$$s(t+jm) = \int_{-\infty}^{+\infty} S(f)e^{-2\pi mf}e^{2\pi ft}df \tag{10}$$

where $S(f)$ is the Fourier Transform of the signal s. Taking the Fourier Transform of the GCM (9), with respect of the lag variable τ, we define the **Generalized Complex Distribution (GCD)** as:

$$GCD_N^K[s](t) = \Im_\tau\left[GCM_N^K[s](t)\right] = \delta\left(\omega-\phi^K(t)\right) * \Im_\tau\left[e^{jQ(t,\tau)}\right] \tag{11}$$

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The GCD has a perfect concentration around the K^{th} order derivative of the phase ϕ but by the convolution, according to ω, with the scattering factor $\Im_{\tau}\left[e^{jQ(t,\tau)}\right]$. If the scattering function $Q(t,\tau)$ is zero (i.e. if all the terms of the derivatives of the order superior to $N+K$ are equal to zero), we obtain an optimal concentration around the theoretical instantaneous phase law. It is important to note that the parameter N of the definition, corresponding to the number of points taken on the contour of the complex integral, allows the reduction of the scattering factor. Actually, the higher N is, the more the terms from the phase derivatives in Q are reduced.

Description of the transient detection method using the GCD

The GCD method is an analysis tool capable to represent, in an optimal manner, and using directly the samples of a signal, the instantaneous phase laws and the phase derivatives for a signal, without taking into account its amplitude.

The detection curve defined from this method will contain the positions and the magnitudes of the maximum arguments of each column of the GCD.

$$DC_{GCD}(t) = \left\{\arg\max\left|GCD(t,f)\right|^2 \geq \beta\right\} \tag{12}$$

Next, we illustrate the efficiency of this detector for the signal defined in the figure 5 and composed of four transients of different values of the amplitudes. As shown by previous examples, the transient with low amplitudes can easily be lost in the detection by the other classic methods (spectrogram, HOS, wavelets) because of their amplitude. In this context, the phase analysis shows its interest for the signals whose phase jumps, caused by the four transients, have the same importance. We use here the analytical signal associated to the real signal, by adding to s an imaginary part generated by Hilbert transform. Working with an analytical signal, written as $Ae^{j\varphi(t)}$, makes the phase analysis more coherent.

The representation obtained by the GCD, applied to the signal defined in the figure 5, is illustrated in the figure 12.

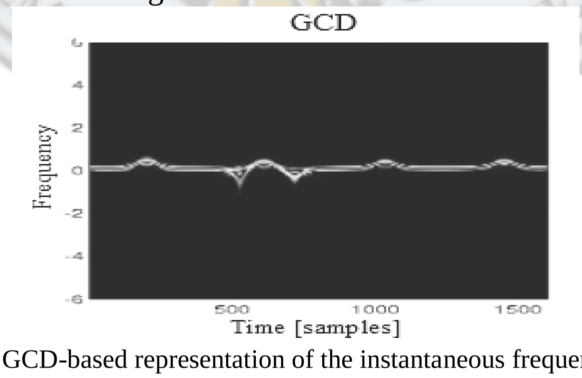

Fig. 12. The GCD-based representation of the instantaneous frequency law (IFL) of the analyzed signal.

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The GCD computes, starting only from the signal's samples, a representation of the signal's IFL. This representation is very well concentrated around the theoretical law we wish to analyze. Being well concentrated around the theoretical law (figure 12), the distribution allows obtaining an accurate detection curve as shown by the figure 13.

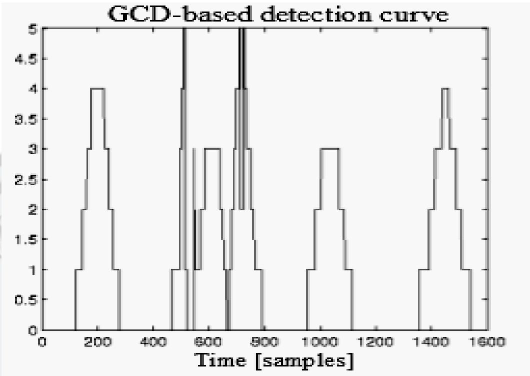
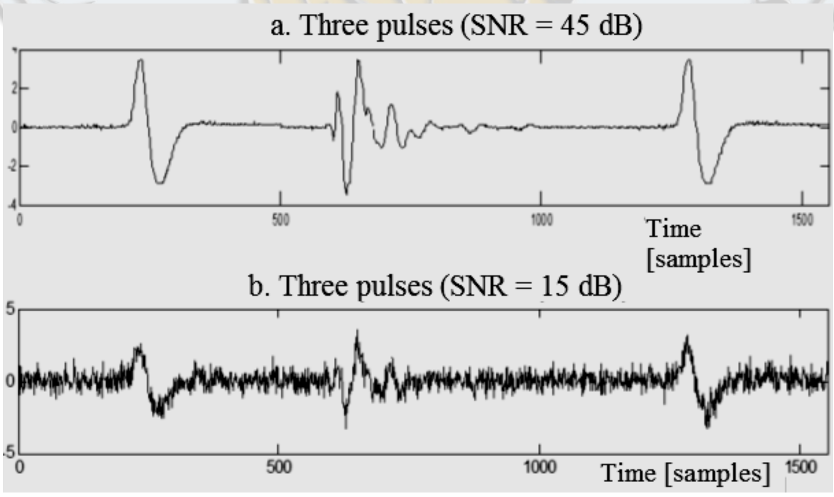


Fig. 13. Detection curve issued from the GCD method.

Despite of the amplitude differences, the GCD outputs a coherent signature, assigning the same gains to the pulses of the analyzed signal. This facilitates choosing the threshold β, ensuring a good compromise between the probability of detection and the probability of false alarm. This result illustrates the efficiency of the complex-time methods to deal with the transient signals issued from electrical systems.

The next example shows, for real transient data, the performing of the three classes of processing methods described in this paper: spectrogram, wavelet transform and GCD. The real signal is a set of three pulses (figure 14.a), the first and the third correspond to a switch transient and the second corresponds to a PD signal. The noised version of such signal is depicted in the figure 14.b.



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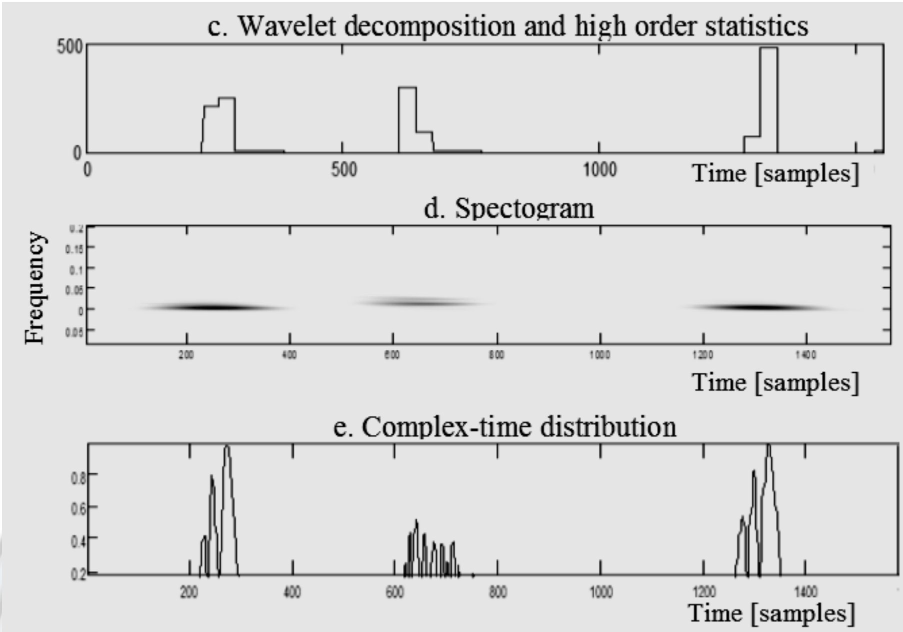

Fig. 14. Detection of the Transient signal composed by three pulses – noise free and noisy versions.

The result plotted in the figure 14.c has been provided by the wavelet packet decomposition combined with the high-order statistics [Rav96]. The detection curve illustrates correctly the three pulses but there is no any indication concerning the similarities or dissimilarities between the pulses. This is also the case of the spectrogram – figure 14.d. The time-frequency content of the pulses is well represented but the distinction between pulses is not straightforward. The figure 14.e shows the results provided by the GCD of order 5. We can see that the pulses are accurately detected and that the similarities between the first and the third pulses are well indicated. The GCD-based representation seems to be well adapted to transient signal analysis and it will be an interesting direction in the context of our projects. The adaptive choice of complex lags is one of the interesting future directions.

Consequently, this example shows the efficiency of the complex-time methodology with respect of the traditional transient signal processing tools.

Conclusions and further works

This paper has been devoted to the illustration of some current techniques for the analysis of transient signals issued from the electrical systems. While the transient signals correspond often to the phenomena that could drastically affect the integrity of the electrical distribution system, their monitoring is an important activity that could be done with help of advanced signal processing tools. Such

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techniques belong to the three classes of methods described in this paper: spectrogram, wavelet transform and GCD. The results showed the effectiveness of these techniques focusing also to the current limitations that could be addressed in our further works.

Namely, the next works will be driven in two directions. First, new representation space for the transient phenomena will be studied. In this field, the complex-time distribution and the phase diagrams are two of the interesting approaches that will be explored. Second, the integration of the physical models describing the electrical phenomena will be also addressed. In this way, we will adapt the further theoretical approaches the specific applications related to the electrical distribution.

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