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COMPLEX-VALUED SIGNAL PROCESSING FOR CONDITION MONITORING

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ABSTRACT

This paper concerns the analysis of stationary complex-valued signals, and its application to the condition monitoring field. More particularly, it is confirmed that usual tools such as correlation function or power spectrum are insufficient to entirely describe the statistical and geometrical properties of complex-valued signals. In that case, additional time and spectral domain quantities, namely the pseudo correlation function and the pseudo spectrum, have to be used. They lead to new important information, and allow to entirely describe second-order properties of complex-valued signals. Once these quantities theoretically defined, this paper describes their use in several condition monitoring problems, where 2 dimensional signals are considered as complex-valued signals. The results obtained in these examples show that these quantities contain crucial information for condition monitoring not given by usual quantities such as the power spectrum, especially in terms of fault localization.

KEYWORDS

Condition monitoring, complex-valued signals, spectral analysis, pseudo spectrum, pseudo correlation.

I. INTRODUCTION

2 dimensional signals are frequently encountered in condition monitoring. Indeed, such signals can be delivered by two sensors measuring a 2D physical quantity (displacement, magnetic field, ...). They can be also the result of mathematical transformations of real-valued signals, as analytic signals or space vectors. The usual way to analyze such signals is to consider each one of their components independently. In that case, the analysis of relations existing between the two components is neglected although this information is often crucial for condition monitoring.

A simple way to take this information into account is to consider such signals as complex-valued by using one component as the real part and the other as the imaginary part. The result is a one dimensional complex-valued signal, which can be analyzed by using signal processing tools, such as spectral analysis.

Second-order analysis tools adapted to stationary complex-valued signals are presented in this paper. More particularly, it is shown in section II that classical tools such as the correlation function and the power spectrum are not sufficient to describe second-order properties of such signals. Additional time and spectral domain quantities, namely the pseudo correlation function and the pseudo spectrum, have to be used. They give access to new important information, and allow to entirely describe second-order properties of complex-valued signals. All these concepts are developed and illustrated through numerical examples in section II.

Next, these tools are used to solve two particular condition monitoring problems. The first one is described in section III and concerns electrical unbalance monitoring of three-phase loads. The second one, developed in section IV, deals with voltage dips monitoring in three-phase power networks. The results obtained show that new second-order quantities such as the pseudo spectrum give access to crucial information for condition monitoring, especially in terms of fault localization.

II. SIGNAL PROCESSING TOOLS FOR COMPLEX-VALUED SIGNALS

II.1. Complex-valued signals

Let $x(t)$ and $y(t)$ be two zero-mean real-valued random signals, supposed to be jointly stationary. A zero-mean stationary complex-valued signal $z(t)$ is then created by setting $x(t)$ as its real part and $y(t)$ as its imaginary part:

$$z(t) = x(t) + jy(t), \quad (1)$$

where $j = \sqrt{-1}$.

In practice, several ways can be envisaged to obtain such a complex-valued signal. For example, $x(t)$ and $y(t)$ can be delivered by two sensors measuring a 2D physical quantity such as a displacement or a magnetic field. $x(t)$ and $y(t)$ can also be the result of mathematical transformations of real-valued signals, as in examples described in sections III and IV.

The complex-valued signal $z(t)$ can be graphically represented in the complex plane, where it follows a curve parameterized by the time index t . Through this representation, the concept of positive and negative frequency is clarified. Indeed, a positive frequency component corresponds to a rotation of $z(t)$ in the counter clockwise or positive sense, while a negative frequency component corresponds to a rotation in the opposite or negative sense. Fig. 1 shows an illustrative example of such a representation. It can be noted that $z(t)$ and its complex conjugate $z^*(t)$ turn in the opposite direction because of the symmetry around the real axis.

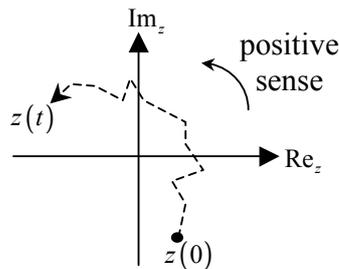


Figure 1: 2D representation of a complex-valued signal $z(t)$

The complex-valued signals considered in what follows being now defined, the following part describes analysis tools specially adapted to such quantities.

II.2. Second-order analysis tools

The statistical description of a complex valued signal $z(t)$ not only necessitates the statistical analysis of $z(t)$, but also the joint analysis of $z(t)$ and $z^*(t)$ [1, 2, 3]. As shown in this part, this fundamental remark leads to additional statistical quantities such as the pseudo correlation function in the time domain, and the pseudo spectrum in the spectral domain. In the following, all signals are supposed to be zero-mean stationary.

Time domain analysis

The classical time domain second-order analysis tool is the so-called correlation function, defined as the correlation coefficient between $z(t)$ and $z(t-\tau)$:

$$C_{zz}(\tau) = E[z(t)z^*(t-\tau)], \quad (2)$$

where $E[\cdot]$ is the mathematical expectation.

Following [1, 2, 3], the pseudo correlation function defined as the correlation coefficient between $z(t)$ and $z^*(t+\tau)$ is also necessary to describe the second-order statistics of $z(t)$:

$$C_{zz^*}(\tau) = E[z(t)z^*(t+\tau)]. \quad (3)$$

It can first be noted from these definitions that the lag τ is added for the pseudo correlation function (Eq. (3)) whereas it is subtracted for the correlation function (Eq. (2)). This fact allows the conservation of the Wiener-Khintchine theorem which links time domain et spectral domain quantities as shown later. Moreover, it can easily be checked that these two quantities are equal and contain exactly the same information in the real case. Indeed, if $z(t)$ is a real-valued signal, the previous equations lead to $C_{zz^*}(\tau) = C_{zz}(-\tau) = C_{zz}(\tau)$ thanks to the symmetry property of the correlation function. This is obviously not true in the complex case.

Some new properties of random signals can be deduced from these definitions [1, 4, 5, 8]. One of them is the properness [4, 5], also called second-order circularity [1]. A complex-valued signal $z(t)$ is proper or second-order circular if $C_{zz^*}(\tau) = 0$, whatever τ . In that case, the second-order statistics of the signal are entirely described by the correlation function $C_{zz}(\tau)$. This is for example the case if the real and imaginary parts of the signal are uncorrelated and have the same correlation function [5], a property usually verified by additive measurement noises present on different sensors.

Eq. (2) and (3) define the temporal quantities used to describe the whole second-order statistics of a complex-valued signal. The next paragraph defines their frequency counterparts thanks to the Wiener-Khintchine theorem.

Spectral domain analysis

The Wiener-Khintchine theorem states that the spectrum $S_{zz}(f)$ of a complex-valued stationary signal $z(t)$ is defined as the Fourier transform of its correlation function:

$$S_{zz}(f) = \text{FT}[C_{zz}(\tau)], \quad (4)$$

where $\text{FT}[\cdot]$ is the Fourier transform.

This spectral quantity has a clear and well-known physical meaning: it represents the repartition of the total signal power in the frequency domain. This explains why the spectrum is a nonnegative real-valued function ($S_{zz}(f) \geq 0$), whatever f .

Similarly, the Fourier transform of the pseudo correlation function leads to an additional spectral quantity $S_{zz^*}(f)$ called the pseudo spectrum:

$$S_{zz^*}(f) = \text{FT}[C_{zz^*}(\tau)]. \quad (5)$$

This spectral quantity is more difficult to understand, but it can be viewed as the cross-spectrum between $z(t)$ and its complex conjugate $z^*(t)$, and represents the joint statistics between these two signals.

Moreover, it has been shown in [1] that $S_{zz^*}(f)$ is a complex-valued even function, which verifies the relation $|S_{zz^*}(f)|^2 \leq S_{zz}(f)S_{zz}(-f)$.

Together, these two functions entirely describe the second-order statistical behaviour of the complex-valued signal $z(t)$ in the spectral domain. It can be noted that if $z(t)$ is real-valued, these quantities are equal and contain the same information. Such tools have been generalized to higher order statistics in [2, 3].

After these theoretical definitions, simple complex-valued signals are analyzed in the next part to understand what kind of information contain each of these quantities.

II.3. Application to synthetic data

Mono-frequency signal

Let $z(t)$ be a mono-frequency zero-mean stationary complex-valued random signal defined by:

$$z(t) = Pe^{j2\pi f_0 t} + Ne^{-j2\pi f_0 t}, \quad (6)$$

where:

- f_0 is the frequency of the complex-valued signal,
- $P = |P|e^{j\angle P}$ and $N = |N|e^{j\angle N}$ are two complex random variables with deterministic moduli and uniform random phases verifying the relation $\angle P + \angle N = \text{constant}$.

Because of the stationary assumption, the random variables P and N verify several properties:

- spectral components with different frequencies are uncorrelated: $E[PN^*] = 0$,
- spectral components have a constant power: $E[|P|^2] = |P|^2$; $E[|N|^2] = |N|^2$,
- spectral components are proper [15]: $E[P^2] = E[N^2] = 0$.

Moreover, the previous properties imply that $E[PN] = |P||N|e^{j(\angle P + \angle N)}$ is a complex-valued deterministic constant.

The signal defined by Eq. (6) can be viewed in the complex plane as the sum of two contra-rotating phasors. The phasor $Pe^{j2\pi f_0 t}$ has a positive frequency and rotates in the positive sense at the rotating frequency f_0 , while the phasor $Ne^{-j2\pi f_0 t}$ rotates in the opposite sense at the same rotating frequency. Here again, the concept of positive and negative frequency is clearly interpreted. It can be shown [6, 7] that such a signal represented in the complex plane rotates around the origin at rotating frequency f_0 in the positive (resp. negative) sense if $|P| > |N|$ (resp. $|P| < |N|$), and follows an ellipse shape as shown in Fig. 2. Moreover, the main parameters of this ellipse, *i.e.* its semimajor axis r_{maj} , semiminor axis r_{min} and inclination angle φ depend on P and N as follows:

$$r_{\text{maj}} = |P| + |N|, \quad r_{\text{min}} = \left| |P| - |N| \right|, \quad \varphi = \frac{\angle P + \angle N}{2}. \quad (7)$$

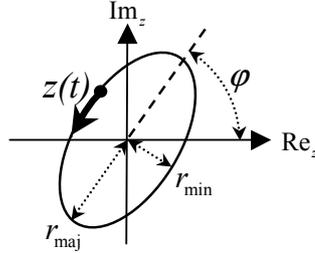


Figure 2: 2D representation of a mono-frequency complex-valued signal

Thanks to the properties of P and N , the parameters defined by Eq. (7) are deterministic. Therefore, they completely characterize the shape followed in the complex plane by the signal (6), whatever its realization. The next paragraph shows how power and pseudo spectra can be used to estimate these parameters and entirely characterize the corresponding shape.

Second-order analysis

The question we have to answer is what kind of information is contained in the second-order analysis tools defined by Eq. (2) to (5) when applied to the previous signal. More precisely, is it possible to easily determine the parameters (7) by applying these tools to a mono-frequency complex-valued signal.

Applying (2) and (3) to (6) and taking Fourier transforms, we obtain the following power and pseudo spectra:

$$S_{zz}(f) = |P|^2 \delta(f - f_0) + |N|^2 \delta(f + f_0) \quad (8)$$

$$S_{zz^*}(f) = |P||N|e^{j(\angle P + \angle N)} [\delta(f - f_0) + \delta(f + f_0)]$$

where $\delta(f)$ denotes the Dirac function.

Eq. (8) shows that the power spectrum and the pseudo spectrum are both necessary to completely characterize the shape followed by the analyzed signal in the complex plane. Indeed, $S_{zz}(f_0)$ and $S_{zz}(-f_0)$ give access to $|P|^2$ and $|N|^2$, and therefore to r_{\min} , r_{\max} and the sense of rotation of $z(t)$. Concerning the evaluation of the inclination angle φ , the phase of the pseudo spectrum has to be used since $\angle S_{zz^*}(\pm f_0) = \angle P + \angle N$.

These results can be further explain thanks to a statistical interpretation of $S_{zz^*}(f)$ given in [2, 3]. In this article, the authors show that if the Fourier transform $Z(f)$ of the complex-valued signal $z(t)$ exists, then $S_{zz^*}(f) \equiv \mathbb{E}[Z(f)Z(-f)]$. This means that the pseudo spectrum can be viewed as the cross-spectrum between spectral components with positive and negative frequency, or equivalently as the correlation between $Z(f)$ and $Z^*(-f)$. Geometrically, this quantity measure the statistical ability of $Z(f)$ and $Z^*(-f)$ to rotate in the same sense [8], which explains why the pseudo spectrum leads to important phase information.

Powerful estimators of $S_{zz}(f)$ have been studied in the literature [9], and the so-called Welch method (time-averaging of $|Z(f)|^2$) will be used in the following. Few results exist concerning the estimation of the pseudo spectrum $S_{zz^*}(f)$, but the previous interpretation suggests that it can be estimated through the time-averaging of $Z(f)Z(-f)$. This estimator is built on the same principle of the Welch method, and will be used in what follows.

Generalization to the noisy case

Let $z(t)$ be the same mono-frequency signal as previously, added with a complex-valued white proper noise $b(t)$:

$$z(t) = Pe^{j2\pi f_0 t} + Ne^{-j2\pi f_0 t} + b(t), \quad (9)$$

where $b(t)$ has a variance σ_b^2 and is uncorrelated with the mono-frequency part of the signal. If $z(t)$ represents a 2D physical quantity measured by two different sensors, the additive noise $b(t)$ can for example model a measurement noise present on each sensor.

Thanks to its properness, $b(t)$ has no influence on the pseudo spectrum and $S_{zz^*}(f)$ is exactly the same as in (8). Concerning the power spectrum, the whiteness of $b(t)$ induces that:

$$S_{zz}(f) = |P|^2 \delta(f - f_0) + |N|^2 \delta(f + f_0) + \sigma_b^2. \quad (10)$$

These theoretical results show that the variance of the additive noise and the parameters of the ellipse followed by the mono-frequency part of the signal (9) can be estimated thanks to power and pseudo spectra of $z(t)$. Indeed, the pseudo spectrum being unchanged, the inclination angle φ is still given by the relation $\angle S_{zz^*}(\pm f_0) = \angle P + \angle N$. Moreover, $S_{zz}(f_0)$ gives access to $|P|^2 + \sigma_b^2$, $S_{zz}(-f_0)$ to $|N|^2 + \sigma_b^2$, and $|S_{zz^*}(\pm f_0)|^2$ to $|P|^2 |N|^2$. All these values can be used to determine σ_b^2 , $|P|$ and $|N|$, and therefore r_{\min} , r_{\max} and the sense of rotation of $z(t)$. An illustrative example is given in Fig. 3, where Fig. 3.a shows the 2D representation of the noisy mono-frequency complex-valued signal to analyze. The ellipse shape followed in the positive sense by this signal is clearly visible, as well as the presence

of a small additive white proper noise. The signal power spectrum and the phase of its pseudo spectrum estimated through the Welch method are represented in Fig. 3.b. The strong spectral components of frequency $\pm f_0$ are easily detectable on the power spectrum. The phase of the pseudo spectrum is only represented for these strong components. By using these spectral quantities, the ellipse parameters are estimated and the corresponding estimated ellipse is shown in Fig. 3.c (red plain curve), superimposed on the original noisy signal (blue dotted curve).

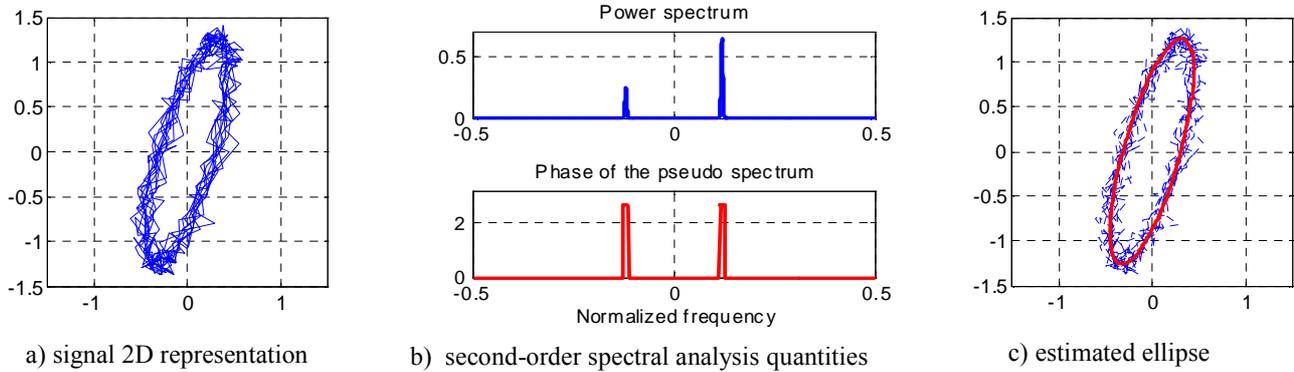


Figure 3: Second-order spectral analysis of a noisy mono-frequency complex-valued signal

This illustrative example is based on a mono-frequency signal, but the power and pseudo spectra being spectral quantities, they obviously can be applied to complex-valued signal with several frequencies. In that case, Fig. 3.b would present several strong spectral components at different frequencies, and the same parameters as in the previous case could be estimated for each of these frequencies.

II.4. Conclusion

The previous example shows that second-order spectral analysis quantities defined by Eq. (4) and (5) are simple and powerful tools to characterize complex-valued signals, even in the presence of noise. They lead to a complete second-order statistical and geometrical description of the analyzed signal, at each frequency. Moreover, the basic structure of the Welch method (time-averaging of windowed Fourier transforms) [9] can be used to elaborate a simple and powerful estimator of the pseudo spectrum.

This work can be viewed as a generalization to the random case of the directional spectrum [6] which as been developed in a pure deterministic case to realise orbit analysis.

The following sections describe some application examples of power and pseudo spectra to condition monitoring problems.

III. CASE 1: UNBALANCE MONITORING IN 3-PHASE LOADS

III.1. Problem statement

This application deals with electrical unbalance monitoring in three-phase loads. More particularly, the example of a induction machine is studied in details. The supplying network is supposed to be balanced and sinusoidal, such that the only component to study is the fundamental component. During the lifetime of the machine, small differences can appear between the stator phases (due to short-circuits in one phase for example). The machine then becomes an unbalanced load and generates unbalanced three-phase currents in the network. Therefore, the electrical unbalance of the machine can be detected and quantified by the measure of the unbalance of the line current three-phase system. In the next paragraph, power and pseudo spectra are used to realise this monitoring task.

III.2. Proposed method

It is well known since Fortescue [10, 14] that unbalanced three-phase systems can be entirely represented and analyzed thanks to their symmetrical components. These components are calculated from the complex amplitudes X_1 , X_2 , X_3 of the three considered line quantities (voltages or currents):

$$\begin{bmatrix} X^P \\ X^N \\ X^0 \end{bmatrix} = \frac{1}{3} \begin{bmatrix} 1 & a & a^2 \\ 1 & a^2 & a \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \\ X_3 \end{bmatrix}, \quad (11)$$

where $a = e^{j\frac{2\pi}{3}}$.

X^P is the positive-sequence component, X^N the negative-sequence component and X^0 the zero-sequence component. The negative-sequence component completely characterizes the unbalance of the studied three-phase system through the ‘‘complex unbalance’’ u defined by:

$$u = \frac{X^N}{X^P}. \quad (12)$$

The magnitude of this complex number $|X^N|/|X^P|$ quantifies (most often in %) the unbalance of the studied three-phase system, while its phase $\angle X^N - \angle X^P$ can be used to localize the phase in fault [10].

The classical way to estimate the unbalance u is to apply a Fourier transform to each line quantity in order to obtain the complex amplitudes X_1, X_2, X_3 of their fundamental component. The unbalance is then determined by Eq. (11) and (12).

Another way to describe a three-phase system is to calculate its instantaneous symmetrical components. They are obtained through the same kind of transformation as previously, but directly applied to the instantaneous line quantities $x_1(t), x_2(t), x_3(t)$:

$$\begin{bmatrix} x^P(t) \\ x^N(t) \\ x^0(t) \end{bmatrix} = \frac{2}{3} \begin{bmatrix} 1 & a & a^2 \\ 1 & a^2 & a \\ 1/2 & 1/2 & 1/2 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \\ x_3(t) \end{bmatrix}. \quad (13)$$

The instantaneous direct-sequence component $x^P(t)$ is a complex-valued signal also called ‘‘space vector’’ [7, 11]. Applied to the same three-phase system as previously, this signal expresses as [12, 13]:

$$x^P(t) = X^P e^{j2\pi f_0 t} + (X^N)^* e^{-j2\pi f_0 t}, \quad (14)$$

where f_0 is the fundamental network frequency.

It can be noted that the positive-sequence component X^P has a positive frequency $+f_0$, while $(X^N)^*$, the complex conjugated negative-sequence component, clearly appears at a negative frequency $-f_0$. Therefore the space vector is a mono-frequency complex-valued signal similar to Eq. (6), and power and pseudo spectra previously defined can be used to precisely estimate $|X^P|$, $|X^N|$ and $\angle X^N - \angle X^P$ even in a noisy case. Once these quantities correctly estimated, the magnitude and phase angle of the complex unbalance u defined by (12) can be easily determined.

In the next paragraph, this method is directly applied to the line currents of a three-phase induction machine in order to monitor its electrical unbalance.

III.3. Experimental results

This experiment was carried out on a 5 kW induction machine supplied with a balanced three-phase voltage system. This machine was unbalanced during its operation (between seconds 10 and 19) by introducing a small additional resistance in one of its phases. The three line currents were acquired synchronously, their shape is shown during a short time duration in Fig. 4.a (without unbalance) and 4.b (with unbalance). The corresponding space vector was obtained by applying Eq. (13) to these currents, and the power and pseudo spectra of this complex-valued signal were estimated through a real-time implementation (sliding FFTs + average). Finally, Fig. 4.c shows the time evolution of the magnitude

unbalance $|u|$ (%) obtained during this experiment from the previous quantities. The phase angle of u were not estimated in this example.

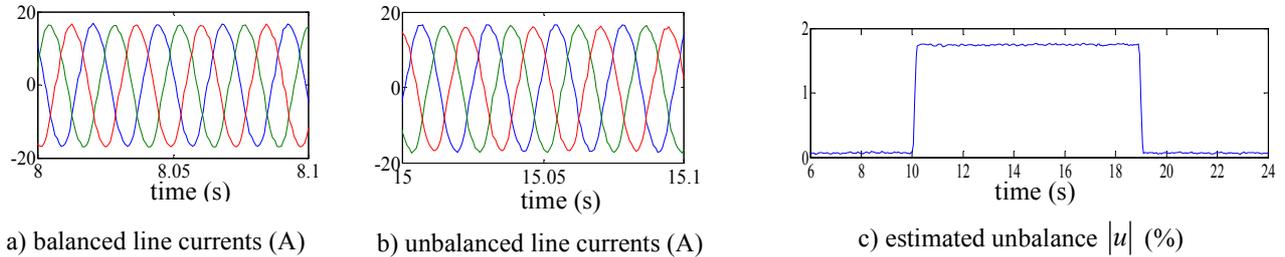


Figure 4: Monitoring of induction machine electrical unbalance through the space vector method

These curves clearly show that $|u|$ correctly represents the quantity of electrical unbalance of the machine as a function of time (about 0.1 % for a balanced machine, and 1.8 % for an unbalanced one). Moreover, this quantity has a low variance when the monitored machine is in a steady-state, while being able to quickly detect a change of unbalance. This performance makes the estimated magnitude unbalance $|u|$ a very suitable quantity to monitor the electrical unbalance of a three-phase load when applied to its three-phase line currents. Moreover, the second-order spectral analysis quantities presented in this paper are simple and powerful tools to estimate this quantity, even in real-time.

IV. CASE 2: VOLTAGE DIPS MONITORING IN POWER NETWORKS

IV.1. Problem statement

In power networks, voltage dips are defined as short duration reductions in voltage magnitude at the fundamental frequency, and are the most common disturbances. They are generated by phase to ground or phase to phase faults that occur at one point of the network. Voltage dips propagate through the network, and can be observed at different locations thanks to voltage sensors. The aim of the present application is to correctly detect, quantify and classify potential voltage dips by analyzing the three line voltages measured at one point of a network, and is based on the work developed in [7].

An observed voltage dip is characterized by its duration, magnitude and phase angle shift on each phase of the network. The last two parameters completely determine the dip type, also called “dip signature”. Obviously, a dip signature depends on power network parameters (system grounding, presence of transformers in the propagation path, ...), on the measurement location, and on fault characteristics (fault type and location in the power network). The most usual voltage dip signatures encountered in power networks has been classified in the literature, leading to the so-called “ABC classification” [10]. A brief description of these different dip types (from type A to G) is given in [7]. In the voltage dips monitoring process, the classification task of the dip type is essential in order to be able to precisely localize, in a further step, the original fault in the monitored network.

IV.2. Proposed method

The space vector transformation defined by Eq. (13) and applied to the three measured line voltages has been successfully used in [7] to monitor voltage dips. In this application, the obtained space vector $v^P(t)$ is a mono-frequency complex-valued signal of frequency f_0 (the fundamental network frequency) which behaves as follows:

- In the flawless case, $v^P(t) = V^P e^{j2\pi f_0 t}$ follows a circle shape in the complex plane.
- In the dip case, $v^P(t) = V^P e^{j2\pi f_0 t} + V^N e^{-j2\pi f_0 t}$ follows an ellipse shape, which parameters r_{\min} , r_{\max} and φ depend on the dip type and characteristics.

This complex-valued signal can be analyzed thanks to power and pseudo spectra as in section II.3 to obtain precise estimates of the ellipse parameters, even in the noisy case. Once these parameters obtained, they are used to realize voltage dips monitoring as follows (see [7] for details):

- r_{\min} is used to detect a potential dip and quantify its depth.
- Once a dip has been detected, its type is determined thanks to r_{\min} , r_{maj} and φ .

IV.3. Experimental results

The performance of the previous method is illustrated in this section through results obtained with data measured on a medium voltage network. Only dips with duration over one cycle are analyzed. Line voltages and space vector characteristics are given in p.u. with respect to the nominal voltage V .

The proposed method is applied to the recorded voltage waveforms presented in Fig. 5.a. The space vector is first calculated from the voltage measurements, and a sliding FFT over one cycle is applied to this complex signal. From these short time spectra, the time evolution of r_{\min} , r_{maj} and φ are determined and represented in Fig. 5 (r_{\min} and r_{maj} in Fig. 5.b, φ in Fig. 5.c).

Next, a segmentation algorithm detects a voltage dip between 0.04 and 0.15 seconds by analysing the evolution of r_{\min} , which decreases below a threshold of 0.9 p.u. (see Fig. 5.b). All curves of Fig. 5 are bold during this period. During the dip, the ellipse inclination angle φ stays near 180° (red bold markers in Fig. 5.c), which indicates a double phase voltage dip. The ellipse major axis $r_{\text{maj}} = 0.85$ is clearly lower than 1, and finalizes the classification step with a dip type set to G. Finally, the ellipse minor axis being $r_{\min} = 0.5$ p.u., the characterization step evaluates the dip depth at approximately 0.41 p.u..

These results are coherent with voltage waveforms of Fig. 5, where it can be seen that two phases are mainly in drop (double phase dip), and their drop is around 0.4 p.u..

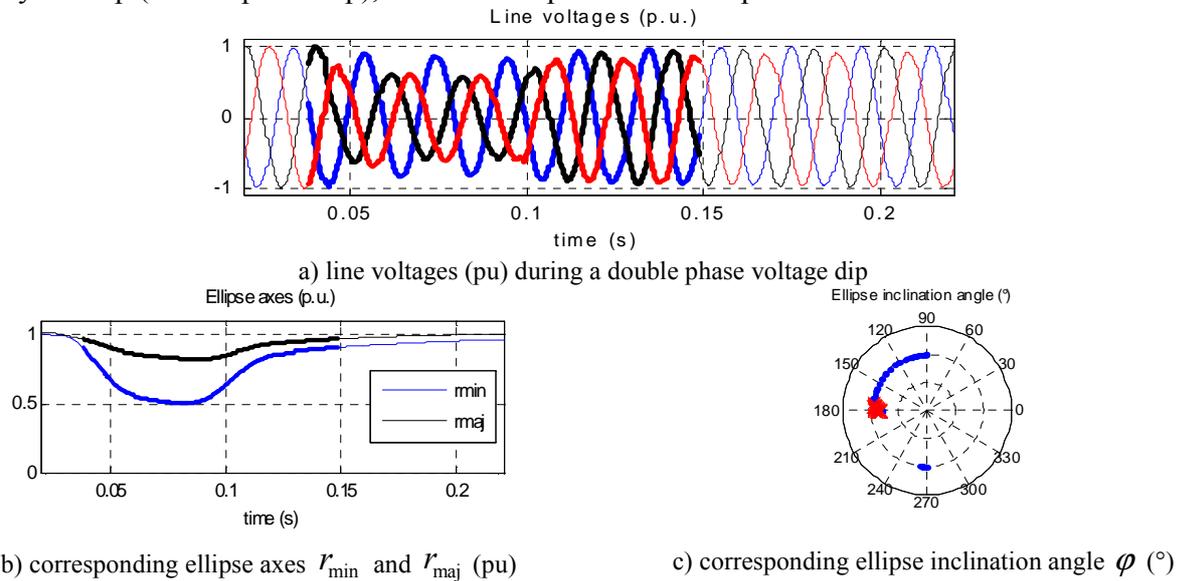


Figure 5: Monitoring of three-phase voltage dips through the space vector method

VI. CONCLUSION

This paper is devoted to the analysis of stationary complex-valued signals, and its application to condition monitoring. First, the theoretical definition of second-order time and spectral domain quantities has been given. Usual tools such as correlation function or power spectrum are insufficient to

entirely describe the statistical and geometrical properties of complex-valued signals. Indeed, important information is contained in unusual quantities called the pseudo correlation function or the pseudo spectrum. For example, it has been shown that the pseudo spectrum contains important phase information about periodic complex-valued signal not given by the power spectrum alone. Another interesting property of this quantity is that it is not affected by additive proper noise and can be used to eliminate its influence. Simple estimators of these spectral quantities have been proposed. They are based on the Welch method, and easily lead to off-line (windowed FFT+average) or real-time (sliding windowed FFT+average) implementation. Second, two different applications of these concepts has been developed in the field of condition monitoring. The first one concerns electrical unbalance monitoring of three-phase loads, and the second one deals with voltage dips monitoring in three-phase power networks. In these two cases, a complex-valued signal is constructed from three-phase measurements, and analyzed thanks to power and pseudo spectra. These tools extract all the information needed to realize the monitoring task (fault detection, quantification and localization), and finally reach good performance. Several direct applications of this method can be envisaged for condition monitoring. Indeed, 2D quantities are often encountered in this field (movement, magnetic field, ...) and are completely equivalent to complex-valued signals which have to be analyzed thanks to the previous tools. The analysis of rotating machine orbits, or the analysis of electrical systems magnetic stray field measured by 2D sensors constitute first examples.

Two main directions can be further explored in future works. First, these tools can be easily extended to multi-sensor analysis, leading to pseudo cross-spectrum and pseudo coherence function for complex-valued signals. These quantities should contain useful and complementary information with respect to classical cross-spectrum and coherence function. Second, physical quantities encountered in condition monitoring problems are most often three dimensional quantities. In that case, complex signals are not sufficient to completely characterize them, but a quaternionic signal could do the job. It should also be noted that in that case, signal processing tools used to analyze this quantity must be adapted.

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