Identification of power quality disturbances using the MATLAB wavelet transform toolbox

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Abstract**: This paper presents an approach that is able to provide the detection and location in time as well as the identification of power quality problems present in both transient and steady-stable signals. The method was developed by using the discrete wavelet transform (DWT) analysis. The given signal is decomposed through wavelet transform and any change on the smoothness of the signal is detected at the finer wavelet transform resolution levels. Later, the energy curve of the given signal is evaluated and a relationship between this energy curve and the one of the corresponding fundamental component is established. The paper shows that each power quality disturbance has unique deviations from the pure sinusoidal waveform and this is adopted to provide a reliable classification of the type of disturbance.**
Key words: power quality disturbances, discrete wavelet transform, signal processing.

1. INTRODUCTION

It is well known that the main power quality deviations are caused by short-circuits, harmonic distortions, notchings, voltage sags and swells, as well as transients due to load switching. In order do correct such problems, it is required, in general that, firstly, they should be detected and identified. Nevertheless, whenever the disturbance lasts for only for a few cycles, a simple observation of the waveform in a busbar may not be enough to allow one to recognise that *there is a problem* in there or, more difficult yet, *to identify* the sort of the problem.

On the other hand, the wavelet transform has been adopted if different fields, such as telecommunications and acoustics. In the last decade the wavelet transform has been studied to analyse voltages and currents during short duration disturbances. The main purpose of this paper is to show an approach in which the MATLAB wavelet transform toolbox is adopted not only to detect power quality problems but also *to classify* them.

2. DISCRETE WAVELET TRANSFORM

The discrete wavelet transform (DWT) is one of the three forms of wavelet transform. It moves a time domain discritized signal into its corresponding wavelet domain. This is done through a process called "sub-band codification", which is done through digital filter techniques. In the signal processing theory, to filter a given signal *f(n)* means to make a *convolution* of this signal. This is illustrated in Fig. 1: the *f(n)* signal is passed through a low-pass digital filter ($h_d(n)$) and a high-pass digital filter ($g_d(n)$). After that, half of the signal samples are eliminated. This is indicated by the symbol ↓2 in Fig. 1.

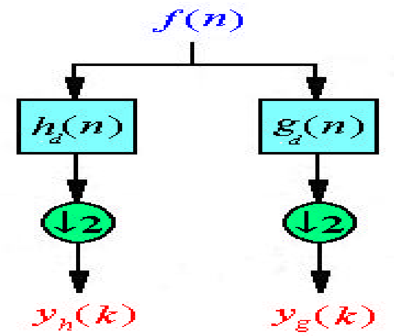


Fig. 1 – Sub-band codification scheme of a signal

Basically, the DWT evaluation has two stages. The first consists on the *wavelet coefficients* determination. These coefficients represent the given signal in the wavelet domain. From these coefficients, the second stage is achieved with the calculation of both the *approximated* and the *detailed* version of the original signal, in different levels of resolutions, in the time domain.

At the end of the first level of signal decomposition (as illustrated in Fig. 1), the resulting vectors $y_h(k)$ and $y_g(k)$ will be, respectively, the *level 1 wavelet coefficients of approximation* and *of detail*. In fact, for the first level , these wavelet coefficients are called $cA_1(n)$ and $cD_1(n)$, respectively, as stated bellow [1]:

$$cA_1(n) = \sum_k f(n).h_d(-k+2n) \tag{1.a}$$

$$cD_1(n) = \sum_k f(n).g_d(-k+2n) \tag{1.b}$$

Next, in the same way, the calculation of the approximated ($cA_2(n)$) and the detailed ($cD_2(n)$) version associated to the level 2 is based on the level 1 wavelet coefficient of approximation ($cA_1(n)$). The process goes on, always adopting the "n-1" wavelet coefficient of approximation to calculate the "n" approximated and detailed wavelet coefficients. Once all the wavelet coefficients are known, the discrete wavelet transform in the time domain can be determined. This is achieved by "rebuilding" the corresponding wavelet coefficients, along the different resolution levels. This procedure will provide the *approximated* ($a_j(n)$) and the *detailed* ($d_j(n)$) version of the original signal as well as the corresponding *wavelet spectrum* [4].

3. THE APPROACH DEVELOPED

By using the DWT and observing the particular features of the several decomposition levels of a signal, some important conclusions of it can be drawn. These information can be used to detect, to locate and to classify the disturbance. A digital program was developed and implemented in the wavelet toolbox of the MATLAB platform, through five steps, as follows:

Step 1: Evaluation of the wavelet coefficients of the signal in study.

Step 2: Evaluation of the square of the wavelet coefficients found at step 1.

Step 3: Calculation of the distorted signal energy, in each wavelet coefficient level.

The "energy" mentioned above is based on the *Parseval's theorem*: "the energy that a time domain function contains is equal to the sum of all energy concentrated in the different resolution levels of the corresponding wavelet transformed signal". This can be mathematically expressed as [2,3]:

$$\sum_{n=1}^{N} |f(n)|^2 = \sum_{n=1}^{N} |a_J(n)|^2 + \sum_{j=1}^{J} \sum_{n=1}^{N} |d_j(n)|^2 \qquad (2)$$

Where:

$f(n)$: Time domain signal in study

N: Total number of samples of the signal

$\sum_{n=1}^{N} |f(n)|^2$: Total energy of the $f(n)$ signal

$\sum_{n=1}^{N} |a_J(n)|^2$: Total energy concentrated in the level "j " of the approximated version of the signal.

$\sum_{j=1}^{J} \sum_{n=1}^{N} |d_j(n)|^2$: Total energy concentrated in the detailed version of the signal, from levels "1" to "j".

Step 4: In this stage the steps 1, 2 and 3 are repeated for the corresponding "pure sinusoidal version" of the signal in study.

Step 5: The total distorted signal energy of the signal in study (found in step 3) is compared to the corresponding one of the pure signal version (evaluated in step 4). The result of this comparison is a *deviation* that can be evaluated by (3):

$$dp(j)(\%) = \left[\frac{en\_dist(j) - en\_ref(j)}{en\_ref(7)} \right] * 100 \qquad (3)$$

where:

j: wavelet transform level

dp(*j*) (%): Deviation between the energy distributions of the signal in study and its corresponding fundamental sinusoidal wave signal, at each wavelet transform level

en_dist(*j*): energy distribution concentrated in each wavelet transform level of the signal in study

en_ref(*j*): energy distribution concentrated in each wavelet transform level of the correspondent fundamental component of the signal in study;

en_ref(7): energy concentrated at the level 7 (which concentrates the highest energy) of the corresponding fundamental component of the signal in study

As to be shown in the next section, the "*dp*(*j*) (%) x *wavelet levels*" curve of every particular power quality disturbance has an unique pattern that can be used to identify the problem in the voltage waveform.

4. STUDY OF CASES

4.1) <u>Detecting and localizing in time a disturbance</u>:

The wavelet adopted in this study was the "Daub4" [4], which is shown in Fig. 2.

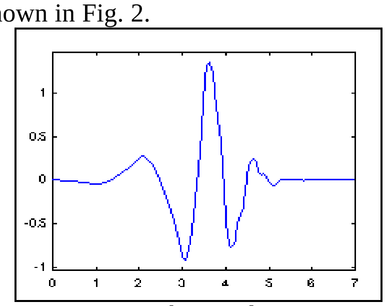


Fig. 2 – Daub4 wavelet

The Fig. 3(a) shows a voltage which was distorted by a capacitor bank switching which has occurred at t= 400 ms (the simulation of this switching was done in the SABER simulator [5]). Fig. 3(b) till 3(g)) summarise the steps 1 and 2 of the approach, as follows. Figs. 3(c), (d), (e), (f), (g) show the squared wavelet detailed coefficients for levels 5, 4, 3, 2 and 1, respectively. Fig. 3(b) illustrates the approximated version of level 5.

The level 1 of the transformed signal (fig. 3(g)), clearly shows a peak at t= 400 ms. The other wavelet levels have also experienced variations at this same instant. This implies that some transient phenomena has occurred here. Therefore, it can be said that the disturbance has been detected and located in time. However, so far, there is no sufficient evidences of *what* sort of disturbance occurred at this signal. This will be discussed in the following subsection.

4.2) <u>Identifying the disturbance</u>:

In order to try to identify the type of disturbance present in the voltage signal of Fig. 3(a), the the step 3 has to be work out. In this step, through equation (2), the energy concentrated in 10 wavelet coefficient levels is calculated and plotted. The results are in Fig. 4(a). The 7th level holds the biggest part of the signal energy. The 6th level also keeps also a important parcel of it. The remaining levels practically do not add any important parcel to the signal energy.

After this, in step 4, the fundamental component of Fig. 3(a) voltage is evaluated as well as the corresponding energy distribution. This is illustrated in Fig. 4(b). After this, if a visual comparison was made between Figs. 4(a) and 4(b), no important differences could be observed. However, these figures are not equal. In order to spot these differences, the equation (3) is required. This equation allows the calculation of the deviation between the energy distributions of the signal in study (Fig. 4(a)) and its corresponding fundamental sinusoidal wave signal (Fig. 4(b)), at each wavelet transform level The result of this is the *deviation curve*, illustrated in Fig. 4(c). This curve "magnify" the deviations of the signal with disturbance from the corresponding pure sinusoidal one. The curve of Fig. 4(c) is within the "pattern" for capacitor bank switching. This will be shown in the next section.

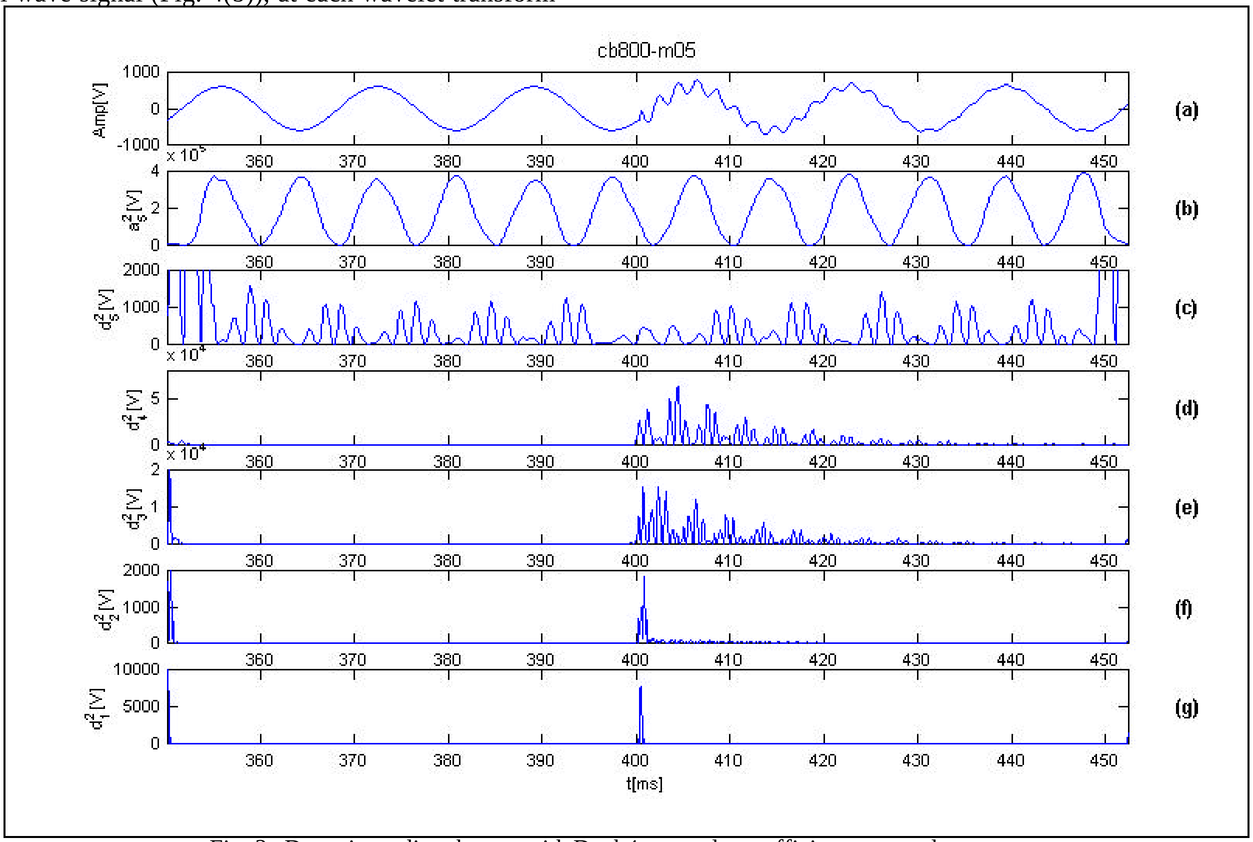
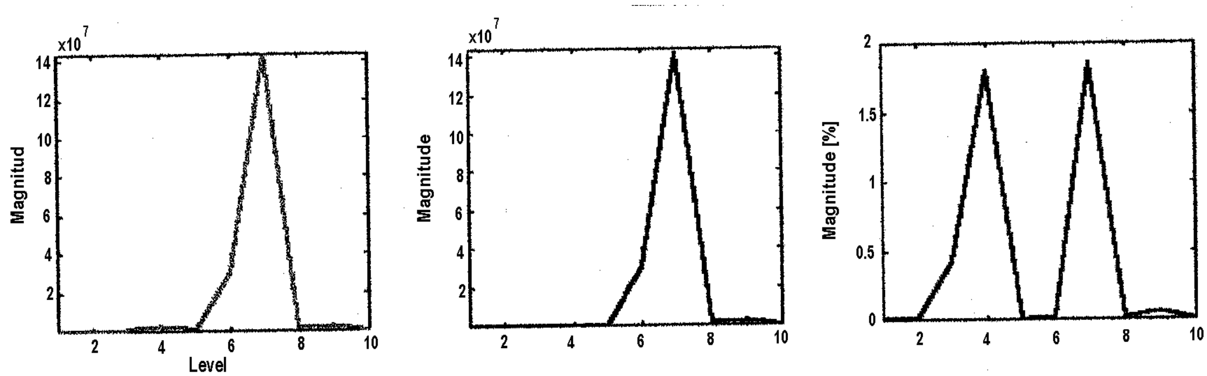


Fig. 3– Detecting a disturbance, with Daub4 – wavelet coefficients squared.;
(a): Voltage signal in study; (b): wavelet approximated coefficient for level 5,
(c) (d) (e) (f) and (g): wavelet detailed versions for levels 5, 4, 3, 2, and 1.



(a) (b) (c)

Fig. 4- Distribution of energy in 10 wavelet coefficient levels
(a) Energy Distribution for figure 2(a) voltage;
(b) Energy Distribution for the fundamental component of figure 2(a) voltage
(c) Deviation between figures 3(a) and 3(b) energy distributions

5. GENERALISING THE CLASSIFICATION PATTERN

The analysis of the capacitor bank switching, shown in the previous section, can be expanded to other power quality disturbances. Fig. 5 shows eight voltage signals that where analysed according to the steps 1 to 5. Fig. 5(a) illustrates the perfect fundamental voltage waveform, which is adopted as a reference for the deviations experienced by the other seven voltage signals of figure 5. The other figures illustrate the most ordinary power quality disturbances, as follows: a short-circuit fault (Fig.5(b)), a notching distortion (Fig.5(c)), a harmonic distortion (Fig.5(d)), a voltage sag (Fig.5(e)), a voltage swell (Fig.5(f)), a capacitor bank switching transient (Fig.5(g)) and a inductive-resistive load switching (P+jQ) (Fig.5(h)).

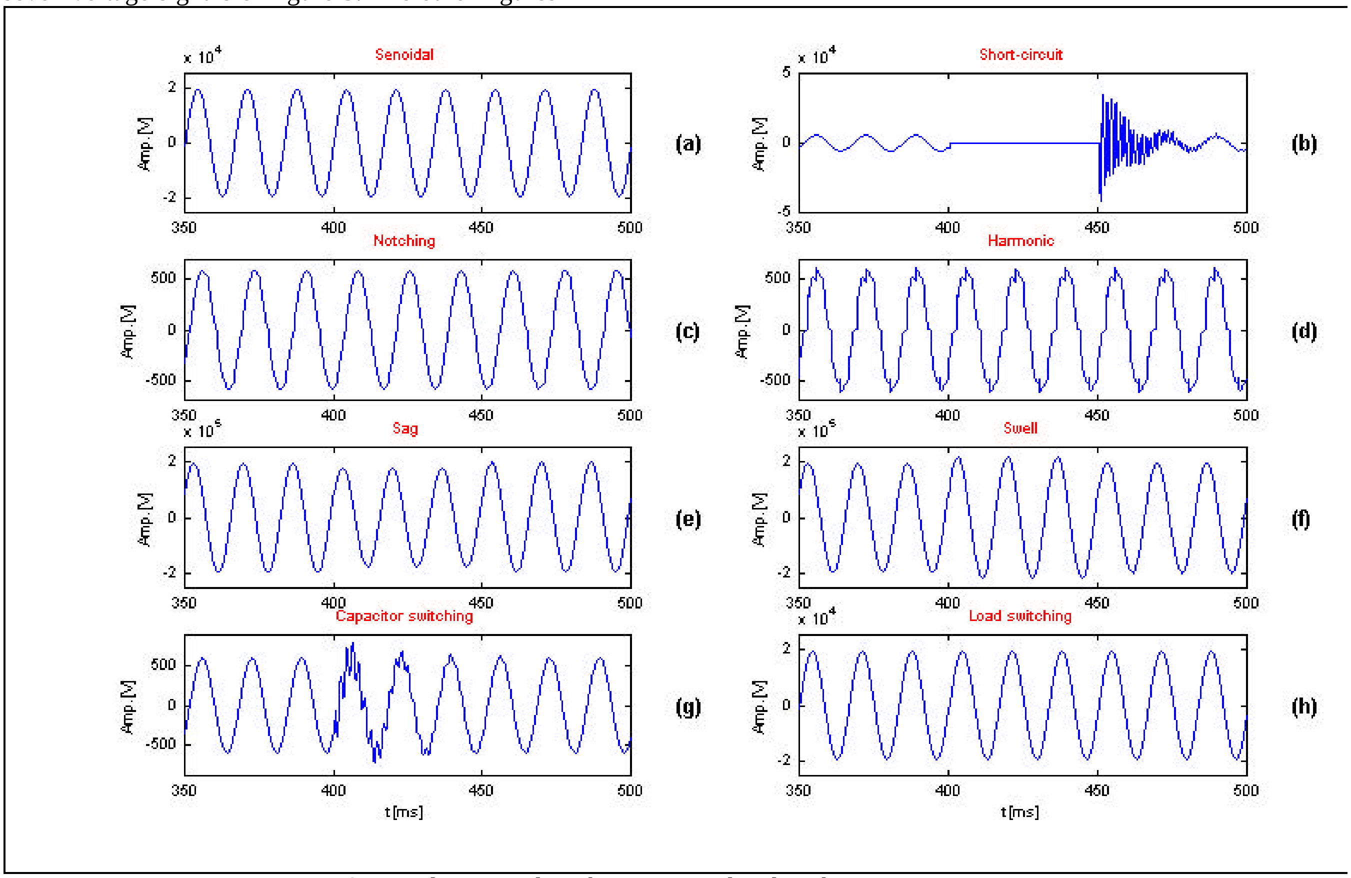


Fig. 5: Some voltage signals with a power quality disturbance
(a): Study reference: pure sinusoidal wave; (b): a short-circuit event; (c) a notching disturbance; (d): a harmonic distortion; (e): a voltage sag; (f):a voltage swell; (g): a capacitor bank switching transient; (h): an inductive-resistive load switching transient

All the procedures related in section 4 for the capacitor bank transient switching were repeated to all Fig. 5 curves. The final results are summarised in the "Distribution of energy deviation" curves illustrated in Fig. 6. For instance, Fig. 6(a) does not show any deviation from the sinusoidal signal because it refers exactly to the Fig. 6(a) pure sinusoidal. However, the other curves (Fig. 6(b),...,6(h)) indicate different deviation patterns from the pure sinusoidal waveform. These features are unique for each disturbance studied an they can be adopted as "patterns" or "signatures" for each disturbance.

Fig. 7 can help to clarify this statement. This figure shows seven different "curve families" of power quality disturbances. Each one of these families were built by analysing 24 cases of power quality disturbance of that particular category. The amplitude and the shape of the curves can vary a little due to the fact that the intensity of the disturbance can change in accordance with the point of the measurement. Nevertheless, each family of curves has an unique signature that can be adopted for the power quality disturbance recognition. This can be helpful, for instance, to find the source of the disturbance as well as to correct it.

6. CONCLUSIONS

This paper has shown an approach that, by using some wavelet transform features, it is able to detect and to locate in time, as well as to classify a transient disturbance. It was shown that the power quality disturbances have unique deviations in their curves of energy from their corresponding pure sinusoidal waveform curve of energy. This feature is adopted to provide a classification of the type of disturbance.

The method presented in this paper should be also adopted to identify harmonic loads in distribution systems.

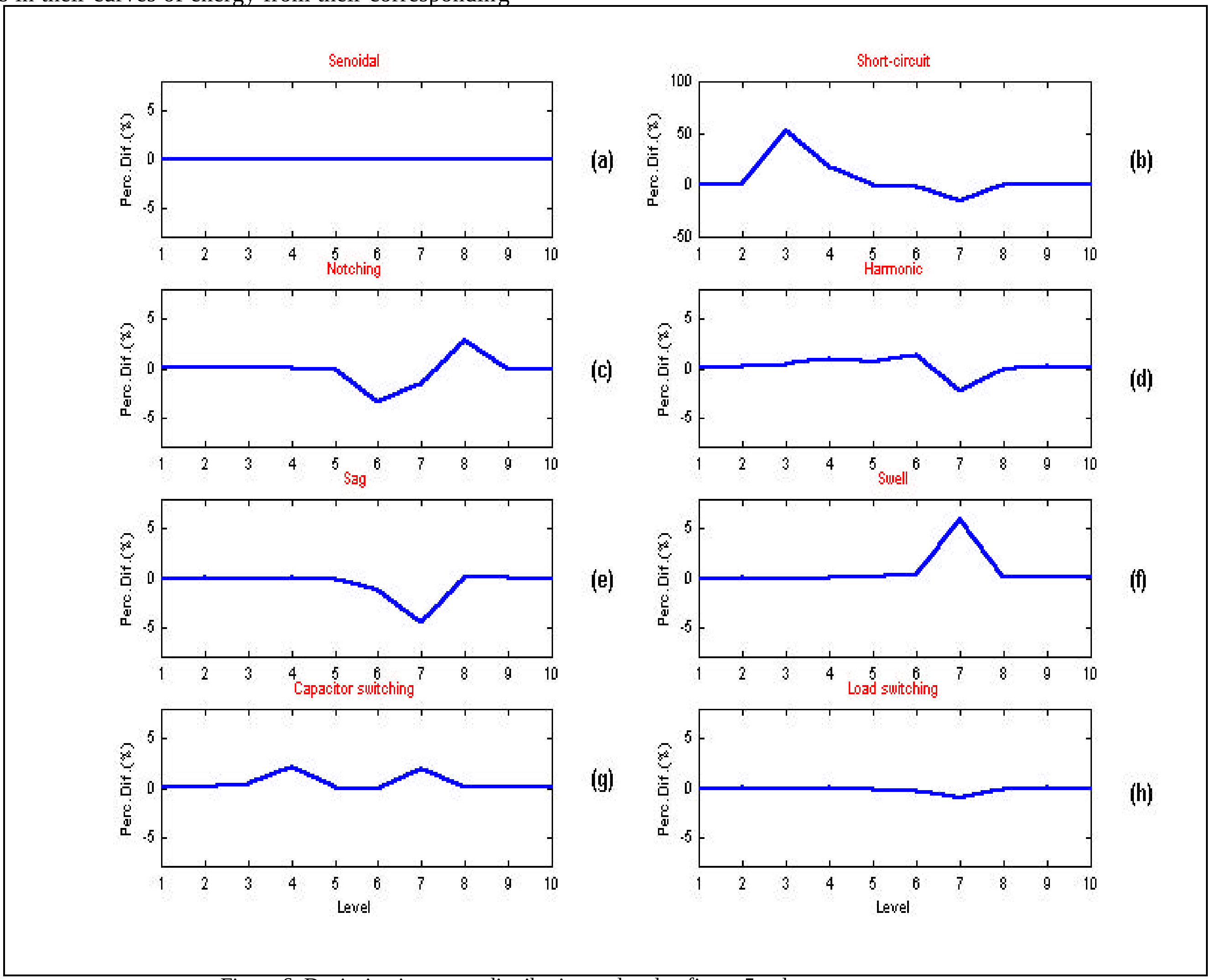


Figure 6: Deviation in energy distributions related to figure 5 voltages
(a): Study reference: pure sinusoidal wave; (b): a short-circuit event; (c) a notching disturbance;
(d): a harmonic distortion; (e): a voltage sag; (f):a voltage swell;
(g): a capacitor bank switching transient; (h): an inductive-resistive load switching transient

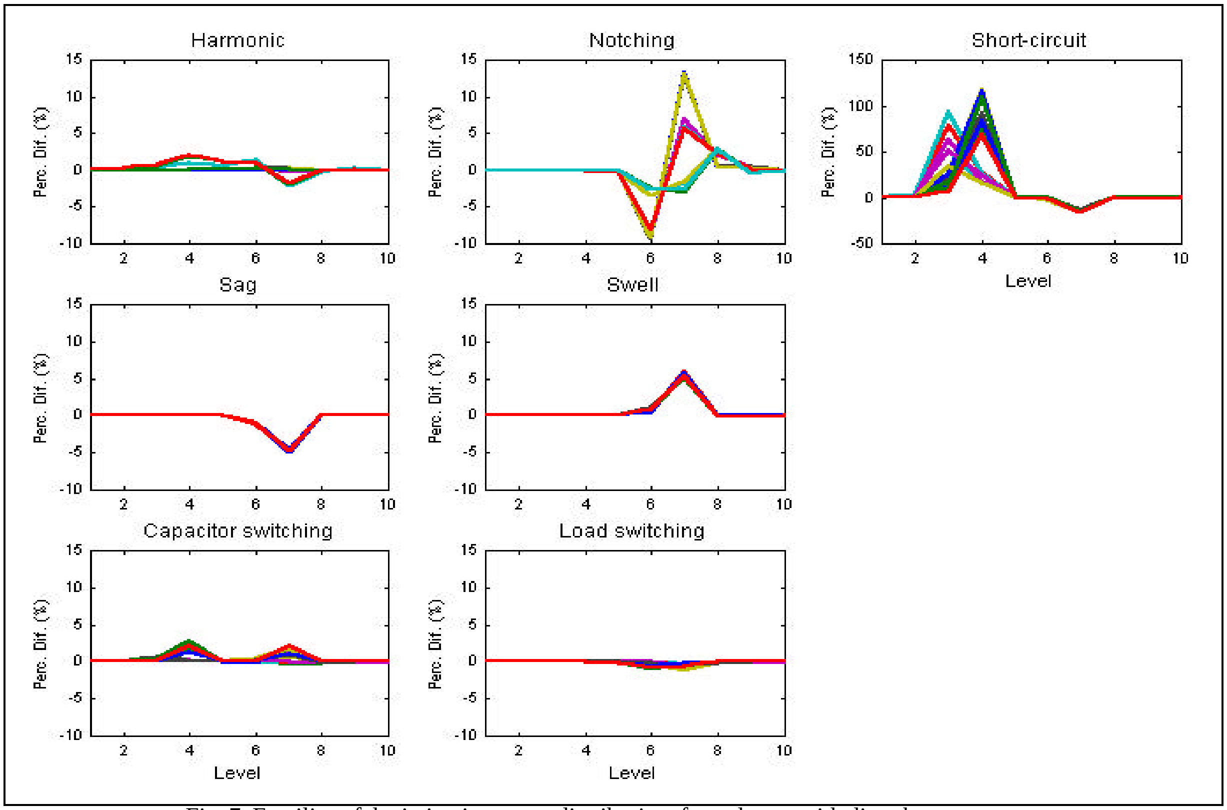


Fig. 7: Families of deviation in energy distribution, for voltages with disturbances
(a): Harmonics; (b): Notching; (c): Short-circuit transients; (d): Voltage sag; (e): Voltage swell;
(f): Capacitor bank switching transients; (g): Inductive-resistive load switching transients

7. REFERENCES

[1] – Robertson, D.C., Camps, O. I., Mayer, J.S., Wavelets and electromagnetic power system transients, *IEEE Transactions on Power Delivery*, Vol. 11, No. 2, April 1996, p.924-930.

[2] – Gaouda, A. M., Salama, M. M. A., Sultan M. R., Chikhani, A . Y., Power quality detection and classification using wavelet-multiresolution signal decomposition, *IEEE Transactions on Power Delivery*, Vol. 14, No. 4, October 1999, p. 1469-1476.

[3] – Burrus, C. S., Gopinath, A. R., Wickerhauser, M. V., Wavelets and time frequency analysis, *Proceedings of the IEEE*, vol. 84, No. 4, April 1996, pp. 523-540.

[4] – Penna, C., Detection and classification of power quality disturbances using the wavelet transform – *M. Sc. Dissertation*, june 2000, Universidade Federal de Uberlandia, Brazil.

[5] – SABER design applications reference, Analogy Inc., july, 1997.