

# Analysis of Electrical Signal Disturbances. A New Strategy

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**Abstract.** A joint treatment for signal analysis based in both Fourier and Wavelet theory is presented. Distinguishing from harmonics and transient disturbance components present on an electrical signal, the former part is extracted by means of Fourier methods, while the latter is subjected to multiresolution treatment in order to split disturbance low frequency components with high frequency components. Numerical experiments are performed over a variety of signals with a given harmonic content, which are classified according to the kind of low frequency disturbance (voltage sag, swell and momentary interruption) and high frequency disturbance (oscillatory transient) present. In every case, a good compression rate is achieved and disturbance components in an efficient way are extracted. Finally, characteristic plots of the low frequency disturbances are obtained for classification purposes.

## Key words

Power quality, harmonics, signal disturbances, FFT, wavelet transform, signal processing.

## 1. Introduction

Since the earliest days of electric power, users have desired that utilities provide electricity without interruptions, surges, and harmonic waveform distortions. Inquiring about such power line disturbances has always been a critical concern for both utilities and users. Recently, however, new sources of disturbances have begun to proliferate, just as many pieces of equipment are becoming more sensitive to these same power disturbances.

Nowadays, only a few percent of utility distribution feeders have a sufficiently severe harmonics problem to require attention [1]. In contrast, voltage sags and interruptions are nearly universal to every feeder and represent the most numerous and significant power quality deviations [2].

In this environment, power quality analysis strategies have usually been divided into those that address steady-state concerns, such as harmonic distortion, and transient concerns, like those resulting from faults or switching transient. Technique such as Fourier spectral analysis are often applied to steady-state events [3-5] while wavelets, classical transient analysis, and computer modeling are traditionally used for transient events [6-10].

### A. Steady-state events

While there are a few cases where the distortion is randomized, most distortion is periodic, or harmonic. That is, it is nearly the same cycle after cycle, changing very slowly, if at all. The advantage of using a Fourier series to represent distorted waveforms is that it is much easier to find the system response to an input that is sinusoidal. Conventional steady-state analysis techniques can be used. The system is analyzed separately at each harmonic. Then the outputs at each frequency are combined to form a new Fourier series, from which the output waveform may be computed, if desired.

Harmonics, by definition, occur in the steady state, and are integer multiples of the fundamental frequency. The waveform distortion that produces the harmonics is present continually or at least for several seconds. Transients are usually dissipated within a few cycles. Transients are associated with changes in the system such as switching a capacitor bank. Harmonics are associated with the continuing operation of a load.

Usually, the higher-order harmonics (above the range of the 25th to 50th, depending on the system) are negligible for power system analysis. While they may cause interference with low-power electronic devices, they are usually not damaging to the power system. It is also difficult to collect sufficiently accurate data to model power systems at these frequencies.

### B. Transient events

Harmonic distortion is blamed for many power quality disturbances that are actually transient. A measurement of the event may show a distorted waveform with obvious high-frequency components. Although transient disturbances contain high-frequency components, transients and harmonics are distinctly different phenomena and are analyzed differently. Transient waveforms exhibit the high frequencies only briefly after there has been an abrupt change in the power system. The frequencies are not necessarily harmonics; they are whatever the natural frequencies of the system are at the time of the switching operation. These frequencies have no relation to the system fundamental frequency.

Continuous and discrete wavelet transform (CWT and DWT) have been used in analysis of non-stationary signals and, recently, several papers [11-13] and books [14-16] have been presented proposing the use of wavelets for identifying various categories of power system disturbances. They are able to remove noise and achieve high compression ratios because of the 'concentrating' ability of the wavelet transform. It has proven a powerful signal processing tool in communications in such areas as, data compression, denoising, reconstruction of high-resolution images, and high-quality speech.

The DWT is implemented using a Multiresolution Signal Analysis (MRA) algorithm [11] to decompose a given signal into its constituent wavelet subbands or levels (scales) with different time and frequency resolution. Each of the signal scales represents that part of the original signal occurring at that particular time and in that particular frequency band. These individual scales tend to be of uniform width, with respect to the log of their frequencies, as opposed to the uniform frequency widths of the Fourier spectral bands. In the common dyadic decomposition to be used, the scales are separated from adjacent scales by a frequency octave. These decomposed signals possess the powerful time-frequency localization property, which is one of the major benefits provided by the wavelet transform. That is, the resulting decomposed signals can then be analyzed in both the time and frequency domains. The MRA is an adequate and reliable tool to detect signal sharp changes and clearly display high frequency transient.

The goal of this work is the use of the wavelet analysis as well as the Fourier analysis for a generic signal (voltage or current signals), in transient or steady state situations, for detecting power quality events. It permits compressing the disturbed signal at higher compression rate than that obtained using the conventional DWT approach, and obtaining characteristic plot signals corresponding to the type of detected disturbance, which is useful for classification purposes.

## 2. Theoretical framework

One of the key features in signal processing is the choice of a suitable basis to represent in an efficient way the kind of considered signals. The Fourier Transform is the main tool for signal spectral decomposition. It represents a signal  $f(t)$  as a superposition of complex exponential of definite frequency  $f$  and infinite time duration, computing the inner products of the signal to be analyzed with the complex exponential, i.e.

$$\hat{F}(f) = \int_{-\infty}^{+\infty} f(t) e^{-i2\pi ft} dt,$$

so the original signal can be recovered by means of the inverse formula

$$f(t) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} \hat{F}(f) e^{i2\pi ft} df$$

Due to this infinite duration of the complex exponential the Fourier Transform describes very well stationary signals, but it is not suitable for non-stationary signals. In order to take into account non-stationary events such as transient disturbances we need to extract somehow the *local* frequency contents of the analyzed signal. To this end, the original signal can be represented approximately as a superposition of *scaling functions*  $\phi_{j0,k}(t)$ , and wavelets  $\psi_{j,k}(t)$ .

$$f(t) = \sum_{k=0}^{2^{J_0}-1} a_{J_0,k} \phi_{J_0,k}(t) + \sum_{j=J_0}^{J-1} \sum_{k=0}^{2^j-1} d_{j,k} \psi_{j,k}(t)$$

where the approximation is truncated at  $j=J-1$ , and sets  $a_{j0,k}$  and  $d_{j,k}$  are the Discrete Wavelet Transform of the signal  $f(t)$ , which can be calculated by

$$a_{J_0,k} = \int_{-\infty}^{+\infty} f(t) \phi_{J_0,k}(t) dt \quad (4)$$

$$d_{j,k} = \int_{-\infty}^{+\infty} f(t) \psi_{j,k}(t) dt \quad (5)$$

In expression (3), the first sum is a coarse representation of  $f(t)$ , where  $f(t)$  has been replaced by a linear combination of  $2^{J_0}$  translations of the scaling function  $\phi_{J_0,0}$ . The remaining terms are the detailed representation. For each  $j$  level,  $2^j$  translations of the wavelet  $\psi_{j,0}$  are added to obtain a more detailed representation of  $f(t)$ .

The wavelet approach is more suitable than the usual Fourier Transform, in those cases in which we are interested in getting good time resolution at the high frequency range for non-stationary signals. It can be viewed as a transformation from the time domain to the time-frequency (*scale*) domain. In wavelet analysis, the scale we use to look at the data plays a special role.

## 3. The proposed method

We now turn to the question of how to perform the desired separated extraction of permanent events, such as the harmonic content and transient events, such as random disturbances (sags, swell, oscillatory transient,...) for a given signal  $f(t)$ . In practice, we never work with the mathematical function  $f(t)$ , but we have partial information concerning it, that is, samples at some regular time interval  $T_s$ . Therefore, our basic input data will be the array

$$f(n) \equiv f(t_n) \equiv f(nT_s), \quad n \in 0, 1, \dots, N-1, \quad (6)$$

where  $N$  is the total number of samples of the signal. The quantities  $T_s$  and  $N$  determine the maximum and minimum frequency we are able to resolve. At one hand, according to Shannon's Theorem, we can not go beyond larger frequencies than  $\omega_{\max} = \omega_s/2$ , where  $\omega_s = 1/T_s$  is the sample frequency. At the other hand, the minimum frequency will be given by the inverse of the time interval in which we have samples of the signal, that is,  $\omega_{\min} = 1/NT_s$ .

First, we proceed to extract the harmonic content using the standard FFT algorithm, that is, we compute the amplitudes  $F_k$  for the definition of the vector  $f(n)$  as a superposition of complex exponential vectors  $e_k(n) = \exp\{i2\pi nk/N\}$ , where  $k \in 0 \dots N-1$ , and  $i$  is the imaginary unit. Each one of this vectors has a definite frequency  $\omega_k = k\omega_{\min}$ , so the mapping from  $k$  to  $\omega$  is given by

$$k \rightarrow \omega_k = \frac{k}{NT_s} \quad (7)$$

The equation then reads

$$f(n) = \frac{1}{\sqrt{N}} \Re \left( \sum_{k=0}^{N-1} F_k e^{-i2\pi nk/N} \right), \quad (8)$$

being the expression for each one of the phasors (FFT)

$$F_k = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} f(n) e^{i2\pi nk/N} \quad (9)$$

The component of the signal  $f(n)$  at the frequency  $\omega_k$  is then given by

$$c_k(n) = |F_k| \cos(2\pi\omega_k t_n + \arg(F_k)) \quad (10)$$

We will define fundamental component of  $f(n)$  as the component corresponding to the value of  $k = k_{\text{fun}}$  such that  $\omega_{\min} k_{\text{fun}} = \omega_0$ , where  $\omega_0$  is some pre-fixed frequency. We shall refer to the *harmonic components* of  $f(n)$  as the components of the Fourier transform corresponding to integer multiples of  $k_{\text{fun}}$ , i.e., those values of  $k$  belonging to the subset  $\Delta = (k_{\text{fun}}, 2k_{\text{fun}}, 3k_{\text{fun}}, \dots, Mk_{\text{fun}})$ , where  $M$  is the highest order for the last harmonic component considered, and it has to be set according to some convention. Finally, we will define the harmonic content of the analyzed signal as the superposition of all the previous components, i.e.

$$h(n) = \sum_{k \in \Delta} |F_k| \cos(2\pi\omega_k t_n + \arg(F_k)) \quad (11)$$

Once we have extracted the harmonic content making use of the previous development, we now consider the extraction of the disturbances at the high and low frequency range. We propose to define the disturbance part of the signal  $f(n)$  as

$$\varepsilon(n) \equiv f(n) - h(n) \quad (12)$$

The definition seems to be natural in the sense that we have removed the harmonic part, computed with the help of the FFT, from the original signal  $f(n)$ . Our main goal will be now two-fold: first, to split with the low and high frequency disturbances respectively, and second, to compact the part  $\varepsilon(n)$ . For this purpose, the Wavelet Analysis turns to be an ideal tool, because wavelet functions are in general able to represent high frequency events with good time resolution, unlike the Fourier Analysis. Therefore we can perform a standard Multiresolution Analysis (MRA) over  $\varepsilon(n)$ , and keep only those  $m$  largest coefficients in the wavelet expression needed to get a pre-fixed precision  $\delta$ , in the sense that

$$\frac{\|\varepsilon(n) - \text{waveapprox}_m(n)\|}{\|\varepsilon(n)\|} \leq \delta, \quad (13)$$

where  $\|\cdot\|$  stands for the usual RN norm and  $\text{waveapprox}_m(n)$  is the wavelet approximation to  $\varepsilon(n)$  using the  $m$  largest coefficients in its wavelet series.

Up to this point, we have been able to represent the original signal  $f(n)$  by  $M$  coefficients corresponding to the harmonic content and  $m$  coefficients corresponding to high and low frequency disturbances. Let us summarize briefly the main steps followed in the previous derivation:

- Calculate  $\omega_{\min}$ ,  $\omega_{\max}$  and  $k_{\text{fun}}$  from the total number of samples  $N$ , the sampling period  $T_s$ , and the fundamental frequency  $\omega_0$ .
- Calculate the FFT phasor  $F_k$ ;  $k \in \Delta$ .
- Select the right values of  $k$  and get the harmonic content  $h(n)$ .
- Define the disturbances at high and low frequency  $\varepsilon(n)$ .
- Perform the MRA over  $\varepsilon(n)$  in order to separate out the low frequency part from the high frequency part and
- approximate it keeping the  $m$  largest coefficients in the wavelet series transformation to get a pre-fixed precision.

## 4. Simulation

In order to illustrate these ideas, we have performed numerical simulations over a variety of signals containing steady-state and transient disturbances. Signals are sampled at  $\omega_s = 6.4\text{kHz}$  during a total interval  $T$  equivalent to 32 cycles. In every case we take as our basis (harmonic) content a fundamental sinusoidal component at 50 Hz, plus its 5th and 7th harmonics, with amplitudes 1, 0.040 and 0.033 pu respectively.

Besides this steady-state event, we have also considered other type transient events taken as *modulating* amplitude of the fundamental component. We have selected, in

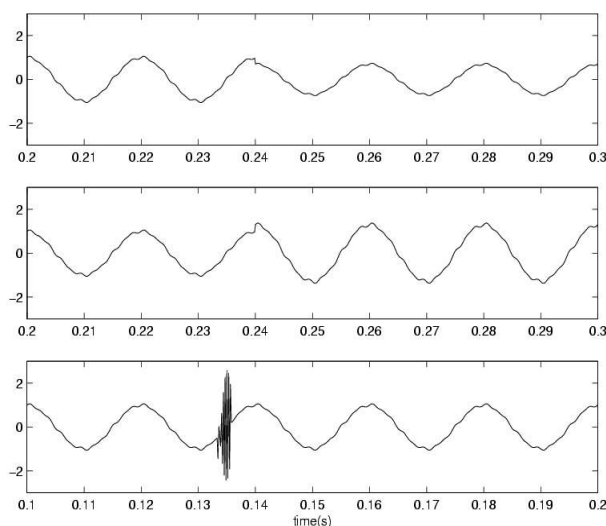


Fig. 1. The three types of considered signals (from the top): sag, swell and oscillatory transient.

virtue of its importance, three typical cases of instantaneous variation (fig. 1):

- The *voltage sag*, represented by a modulating square wave whose effect is to *decrease* by a factor (0.1- 0.9 pu) the signal magnitude over an interval of 0.5- 30 *cycles*. Instantaneous interruption shall be considered here as a special type of sag, having decreased the signal magnitude less than 0.1 pu.

- As the opposite case, we consider a *voltage swell*. In this case, the modulating square wave *increases* by a factor (1.1- 1.4 pu) the magnitude of the signal over an interval of 0.5- 30 *cycles*.

- Finally we also take into account the *oscillatory transient* phenomenon, that is, a sudden non-power frequency change in the steady-state condition of signal including both positive and negative polarity values. Typical spectral content between 5 and 500~kHz (Medium frequency) and duration between 0.02 and 50 *ms*, were considered in the simulation.

Then, results of these methods are presented in figures 2-8. The observation window comprises a time interval of 32 cycles and 256 samples per cycle. This window is appropriate for the study of the above input signals. A convenient threshold is required for detecting the instant when the disturbance starts. In our case, an input signal consisting of sag and oscillatory transient disturbances (Signal 1 in fig. 2) is compared with another input signal consisting of swell and oscillatory transient disturbances (Signal 2 in fig.2). Both signals show magnitude change of 0.3pu for duration of eight cycles, and oscillatory transient of 1.5pu for 1.3ms and 3kHz.

Simulation of the proposed method of signal analysis was performed using the Wavelets Extension Pack of Mathcad. It includes two possible strategies: one applies directly the input signal to the MRA solver, the other extracts previously the harmonic content from the input sampled-signal before applying the MRA. Figure 3 shows the harmonic content (frequency spectrum) common to both input signals, which was calculated using the *fft* Mathcad instruction. According to the second strategy, input signals are filtered to remove the harmonic content so that the resulting waveform is more

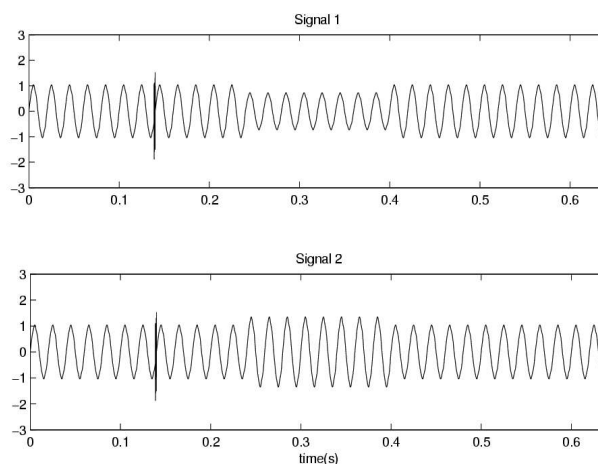


Fig. 2. Input signals considered for testing. Signal1 contains sag and oscillatory transient disturbances; Signal2 contains swell and oscillatory transient disturbances.

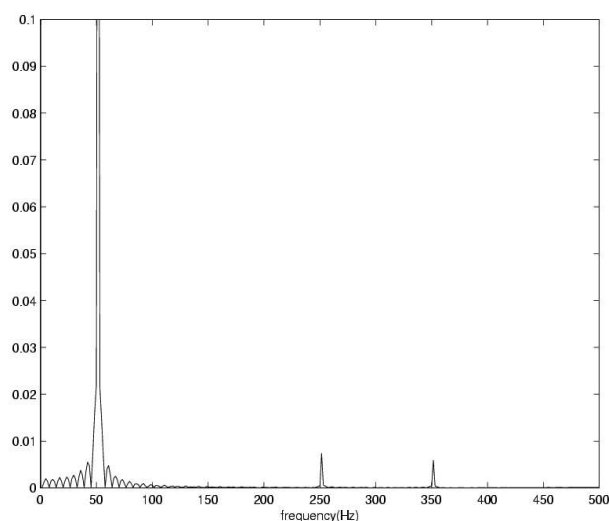


Fig. 3. Spectrum (frequency content) for signals of Fig. 2.

susceptible to compression and classification. Figures 4 and 5 show two components resulting from the analysis of the input signals in the time domain. The signal shown in figure 4 is the inverse FFT of harmonic content shown in figure 3. Signals shown in figure 5 contain disturbances in the low and high frequency bands. In

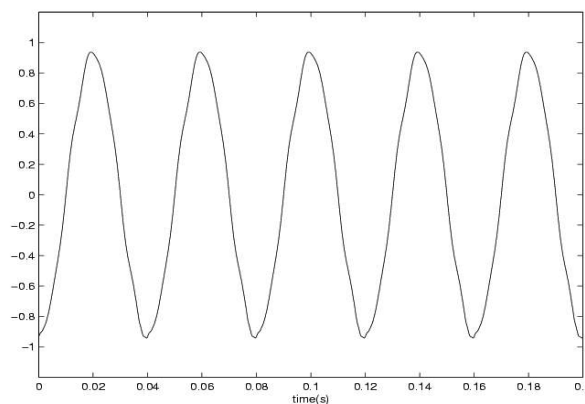


Fig. 4. Harmonic content common to signals of Fig. 2. The calculation has been done selecting the harmonics components from the limited frequency spectrum and taking the inverse Fourier Transform over this subset.

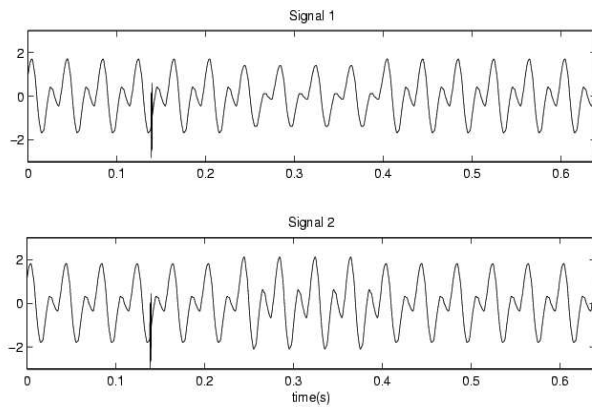


Fig. 5. Disturbances for the sag and swell cases defined as the remaining piece of the original signal after removing the harmonic component.

general, interharmonics and high frequency harmonic components due to the disturbance occurrence constitute this signal.

The wavelet transform further enhances the analysis of these disturbances as shown in figure 6, where a multisignal trace was selected from the MRA results. The DWT used in this simulation (Daubechies family Db4) is applied to a digitized function with  $N = 2^{13} = 8192$  samples, getting signals  $a_j(n)$  and  $d_j(n)$ , where  $j = 13$  is the maximum index level. This family Db4 is particularly appropriate to detect disturbances of high frequency (transient) as it is more localized in time than other members of the same family, for example family Db20.

Each disturbance type produces a characteristic plot, an example of which is shown in figure 7, where low frequency scales 0-2 are added to obtain the signal used

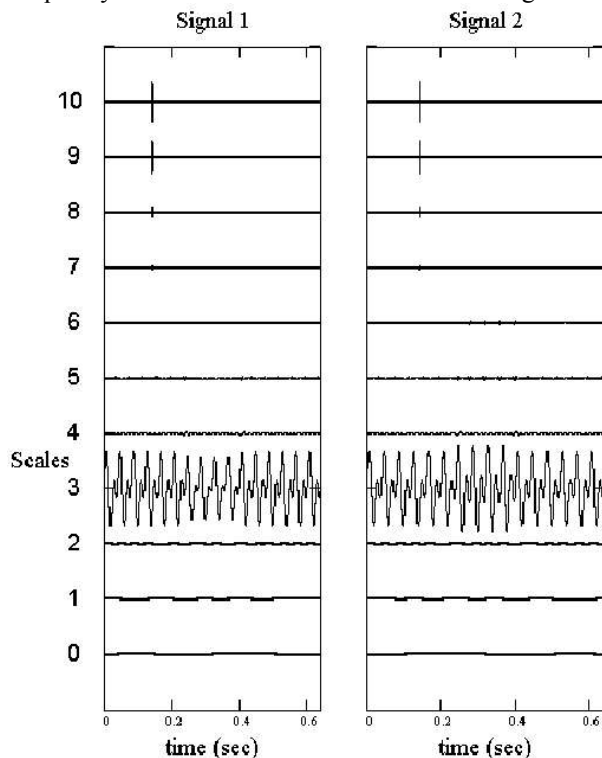


Fig. 6. Mutiresolution analysis of the disturbances (low and high frequency) in the sag (Signal 1) and swell (Signal 2) cases, using the Daubechies-4 basis at ten levels of resolution. Wavelets Extension Pack of Mathcad has been used.

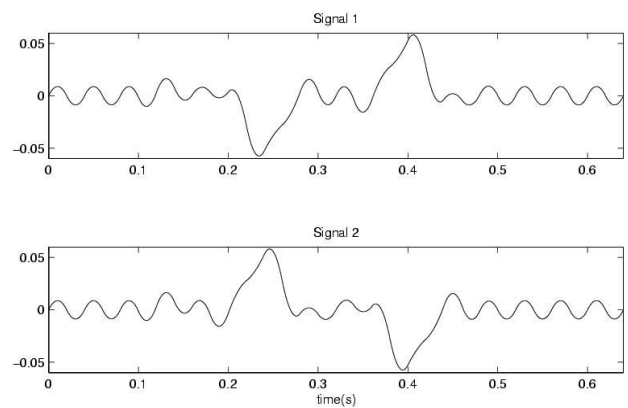


Fig. 7. Characteristic plot for the sag (Signal 1) and swell (Signal 2) cases.

for disturbance classification. So, sag and swell are types of disturbances, which can be classified in the time domain using their characteristic plot as detector.

The algorithm was used for compressing the original input signal, Signal 1 shown in figure 2, and the same signal without the harmonic content, Signal 1 shown in figure 5, for several values of frequency resolution. A significant reduction of coefficients was obtained in the compression process, being more important in the case of the second signal. Thus, for  $J = 10$  and the first signal, the algorithm reduces the signal samples to  $m = 495$  coefficients taking the value  $\delta = 0.01$ . In the same conditions, compressing the signal without harmonic content the algorithm reduces the signal samples to  $m = 390$  coefficients.

For  $\delta = 0.01$ , a perfect reconstruction of the input signal was obtained adding the harmonic content and the compressed signal containing the high and low frequency disturbances. Keeping  $\delta = 0.1$ , the signal is again reconstructed and is observed to be worse than at  $\delta = 0.01$  (fig. 8). It is obvious that with higher  $\delta$  value less data are retained after compression and hence accuracy is sacrificed in reconstructing the signal. However, high  $\delta$  value is preferred from data communication and storage

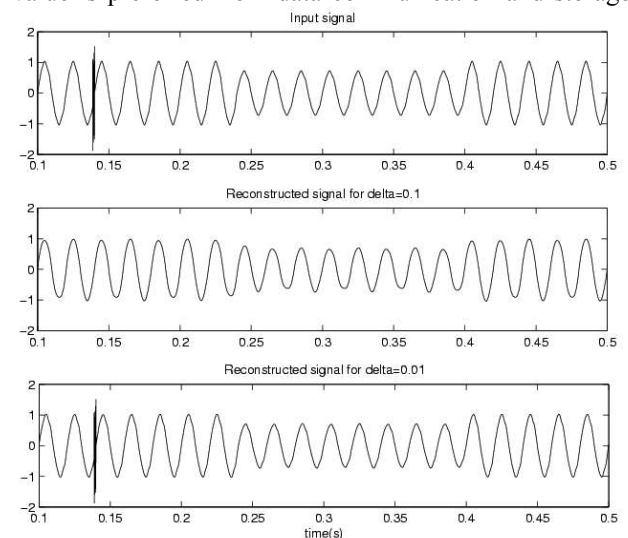


Fig. 8. Approximation of the disturbances in the sag case using the described compression algorithm for the performance index values  $\delta = 0.1$  and  $\delta = 0.01$ .

point of view. Data reduction between input and output signals was calculated according to index [17]

$$\tau = \frac{\text{No. coeff. of compressed signal}}{\text{No. samples of original signal}} \times 100, \quad (14)$$

which is a number satisfying  $0 \leq \tau \leq 100$  and reflecting the efficiency of the method (the closer to zero, the better it is). For the reconstructed signals of figure 8, we get  $\tau = 4.55$  per cent corresponding to index  $\delta = 0.01$ , and  $\tau = 0.38$  per cent corresponding to  $\delta = 0.1$ .

## 5. Conclusion

A power quality analysis strategy has been used to divide steady-state concerns, such as harmonic distortion, and transient concerns. The Fourier and wavelet transforms for the analysis of electrical signals containing steady-state or/and transient disturbances have been used.

Several assumptions were considered:

Waveform distortion that produces the harmonics does not change during the measurement interval.

Harmonics are integer multiples of the fundamental frequency. The harmonic band to be the part of the spectrum within the range defined between the fundamental and its 40th harmonic.

Transients and harmonics are distinctly different phenomena and are analyzed differently.

High frequency transients are usually dissipated within a few cycles.

Low frequency transients can be considered as disturbances with frequencies below the fundamental frequency, taken as modulating amplitude to the steady-state wave.

Frequencies corresponding to transient waveforms are not necessarily harmonics; they are whatever the natural frequencies of the system are at the time of the switching operation. These frequencies have no relation to the system fundamental frequency.

Therefore, in each one of the cases we extract the first forty harmonics of the fundamental component making use of the standard FFT algorithm and perform a MRA analysis over the disturbance part expecting to distinguish between low and high frequency disturbances. Finally, we compress this part according to some prefixed precision.

In order to illustrate these ideas, we have performed numerical simulations over a variety of signals containing steady state and transient disturbances.

We have added to a nonsinusoidal waveform, in virtue of its importance, three common disturbances: the voltage sag, the voltage swell and the oscillatory transient phenomenon. The analysis performed demonstrates the possibilities of the proposed technique. So, the approximated signal in the lower scale, as derived from the wavelet analysis, can be used directly for automatic classification of electrical disturbances such as voltage sags, voltage swells, momentary interruptions, etc.

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