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# Power Quality Data Compression

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## 1. Introduction

Nowadays we assist to the increasing of devices and equipments connected to power systems (non-linear loads, industrial rectifiers and inverters, solid-state switching devices, computers, peripheral devices etc). Hence, the parameters of the power supply should be accurately estimated and monitorized. For this purpose have been proposed power quality monitoring systems that are abble to automatically detect and classify disturbances. They are using the most recent signal processing techniques for power quality analysis (Bollen et al., 2006), (Dungan et al., 2004), (Lin et al., 2009).

A power quality monitoring system provides huge volume of raw data from different locations, acquired during long periods of time and the amount of data is increasing daily. The hardware of a power quality monitoring systems should have a high sampling rate because the power quality events cover a broad frequency range, starting from a few Hz (flicker) to a few MHz (transient phenomenon). A high sampling rate leads to large volume of aquired data (for example, one recorded event could requires megabytes of storage space) which should be transferred and stored. Therefore, it is necessary data compression to save storing space and to reduce the communication time. Any compression methode is a compromise between the resulted volume of data and the remained information. The aim is to obtain the smalest size with the highest information level (Barrera Nunez et al., 2008), (Lorio et al., 2004), (Wang et al., 2005).

In order to compress data there are many approaches used in digital communications and image compression. These may be divided in two broad categories: lossless and lossy techniques. The first category keep the signal information intact. The second category remove redundant information from signals to achieve a higher compression ratio (Ribeiro et al., 2004).

In recent years, the results presented in scientific literature show that the most used compression methods in power quality are based on wavelet transform and Slantlet transform. This chapter will provide an overview of their applications for power quality signals.

## 2. Data compression using wavelet transform

### 2.1. Wavelet transform

The wavelet transform ensures a progressive resolution in time-frequency domain, suitable to track the nonstationary signals dynamics properly. It use a variable window size, wide for low frequencies and narrow for high frequencies, to achieve a good localization in time and frequency domains (Ribeiro et al., 2007), (Zhang et al., 2011).

The Continuous Wavelet Transform (CWT) of a signal $f(t) \in L^2[R]$ is defined as

$$CWT(\tau, \gamma) = \int_{-\infty}^{\infty} f(t) \overline{\Psi_{\tau, \gamma}} (\frac{t - \tau}{\gamma}) dt \tag{1}$$

where $\tau$ is the scale factor, $\gamma$ is the translation factor and $\Psi_{\tau, \gamma}$ is the mother wavelet.

The Fourier analysis decomposes a signal into a sum of harmonics and wavelet analysis into set of functions called wavelets. A wavelet is a waveform of limited duration, usually irregular and asymmetric. These functions are obtained by dilations and translations of a unique function called mother wavelet $\Psi_{\tau, \gamma}$ and the function set $(\Psi_{\tau, \gamma})$ is called the wavelet family

$$\Psi_{\tau, \gamma}(t) = \frac{1}{\sqrt{\gamma}} \Psi(\frac{t - \tau}{\gamma}), \gamma > 0, \tau \in R \tag{2}$$

The Inverse Continuous Wavelet Transform (ICWT) is given as

$$f(t) = \frac{1}{C_\Psi} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} CWT(\tau, \gamma) \Psi_{\tau, \gamma}(t) \frac{d\tau d\gamma}{\tau^2} \tag{3}$$

where $C_\Psi$ is the normalized constant.

In power quality analysis we work with acquired signals. These are discrete-time signals. Moreover, the CWT provides a redundant signal reprezentation in continuous-time, because the initial signal is possible to be reconstructed by a discrete version of CWT. The CWT is evaluated at dyadic intervals: the factor $\tau$ and $\gamma$ are discretezed as $\tau = 2^k$, $\gamma = 2^k n$ where $n, k \epsilon Z$. The relation (2) becomes (Dash et al., 2007), (Qian, 2002)

$$\Psi_{k,n}(t) = 2^{k/2}\Psi(2^k t - n) \tag{4}$$

The wavelet transform is the most used multiresolution analysis (MRA) technique of signals. Multiresolutions signal decompositon is based on subbads decomposition using low-pass filtering and high-pass filtering.

In muliresolution analysis a continuous function $x(t)$ is decomposed as follows

$$x(t) = A_{j_0}(t) + \sum_{j=0}^{j_0} D_j(t) \tag{5}$$

where

$$A_j(t) = \sum_k c_j(k)\varphi_{j,k}(t) \tag{6}$$

$$D_j(t) = \sum_k d_j(k)\psi_{j,k}(t) \tag{7}$$

$c_j(k)$ are the scaling function coefficients, $d_j(k)$ are the wavelet function coefficients, $j_0$ is the scale, $\varphi(t)$ is the scaling function, $A_j(t)$ is called approximation at level $j$ and $D_j(t)$ is called the detail at level $j$ (Azam et al., 2004), (Zhang et al., 2011).

For a given signal $x(t)$ and a three levels wavelet decomposition the relation (5) become

$$\begin{aligned} x(t) &= A_1 + D_1 \\ &= A_2 + D_2 + D_1 \\ &= A_3 + D_3 + D_2 + D_1. \end{aligned} \tag{8}$$

The decomposition of signal $x(t)$ in $A_1$ and $D_1$ is the first decomposition level. At each decomposition level the signal is decomposed into an approximation and a detail.

Each detail $D_j$ reveals details of the signal and each approximation $A_j$ shows corse information. If the analysed signal contains a high frequency event (for instance, a transient phenomenon), the magnitude of details $D_j$ associated with the event are significant larger than the rest of the coefficients. This observation is useful for compressing power quality signals: only the details $D_j$ associated with the events are retained and all other coefficients are discarded. Moreover, the approximation coefficient is also kept for signal reconstruction (Santoso et al., 1997).

## 2.2. Data compression with wavelet transform

A general data compression method based on wavelet decomposition and reconstruction is shown in Fig. 1. That is a lossy compression method which includes certain steps (Wu et al.,

2003), (Hamid et al., 2002), (Littler et al., 1999) : first, the signal is decomposed into several wavelet transform coefficients (WTCs) using the DWT, thresholding of WTCs (useful to extract information and remove redundancy) and finally the signal is reconstructed from the retained WTCs.
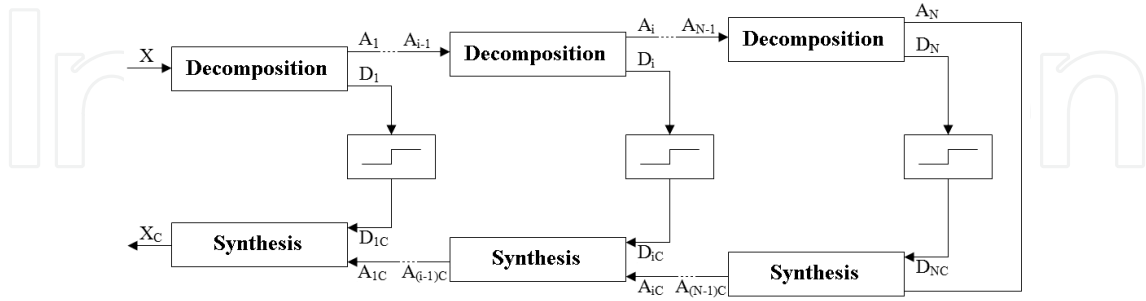


**Figure 1.** A general multi-scale wavelet compression method

One of the methods for the thresholding of WTCs is to set a threshold than only the coefficients above threshold are retained. Those below threshold are set to zero and are discarded (almost 90% of WTCs, some information will be lost). As a result, the amount of stored data is reduced.

The threshold is calculated based on absolute maximum value of the WTCs as

$$\eta_S = (1-u) \times \max\{|D_i(n)|\}$$
(9)

where $u$ take values in the range $0 \leq u \leq 1$ and $s$ is the associated scale.

Thresholding of WTCs is given by

$$D_{iS}(n) = \begin{cases} D_i(n), & |D_i(n)| \geq \eta_s \\ 0, & |D_i(n)| < \eta_s \end{cases}$$
(10)

and the retained WTCs are stored together along with their temporal positions.

To evaluate the performance of signal compression are used the compression ratio (CR) and the normalized mean-square error (NMSE).

The data compression ratio is defined by

$$CR = \frac{S_o}{S_c}$$
(11)

where $S_o$ is the size of original file and $S_c$ is the size of compressed file.

The quality of reconstructed signal is evaluated using the normalized mean-square error which is defined as

$$NMSE = \frac{\|X(n) - X_C(n)\|^2}{\|X(n)\|^2} \tag{12}$$

where $X(n)$ is the original signal and $X_c(n)$ is the compressed signal. A low value of NMSE corresponds to a small error between the original and reconstructed signal.

In the sections 2.2.1-2.2.2 is tested the performances of the general multi-scale wavelet compression method for transient phenomena and voltage swell. The influence of the order of Daubechies scaling function and the number of decomposition levels on data compression are analysed. The signals are simulated in Matlab environment. The details and the results are presented below.

### 2.2.1. Transient phenomena

Transient phenomena are sudden and short-duration change in the steady-state condition of the voltage, current or both. These are classified in two categories: impulsive and oscillatory transient (Fig. 2). The first category has exponential rise and falling fronts and it is characterized by magnitude, rise time (the time required for a signal to rise from 10% to 90% of final value), decay time (the time until a signal is greater than ½ from its magnitude) and its spectral content. The second category is characterized by magnitude, decay time and predominant frequence (Dungan et al., 2004), (Găşpăresc, 2011).
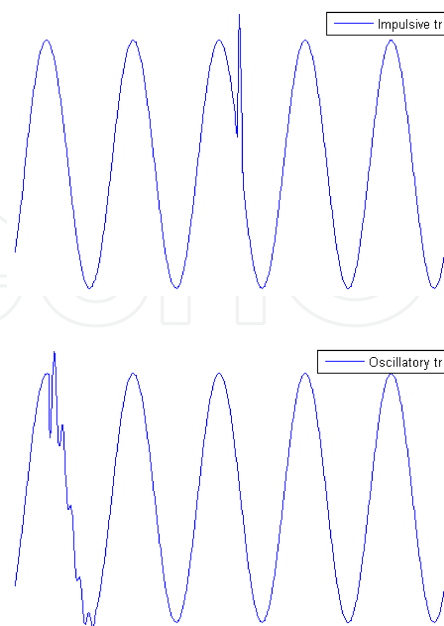


**Figure 2.** Transient phenomena

Fig. 3 shows the first test signal, an impulsive transient with magnitude of 1000 V superimposed on a sinusoidal signal with amplitude of 230 V and frequency of 50 Hz, corrupted with additive white noise. The sampling rate is 20 kHz. The signal is decomposed into three, four and five levels based on wavelet decomposition (Daubechies scaling function of order 3rd, 4th and 5th is used). Than the signal it is compressed using the threshold values 1, 5, 7 and 10. The results are presented in table 1.
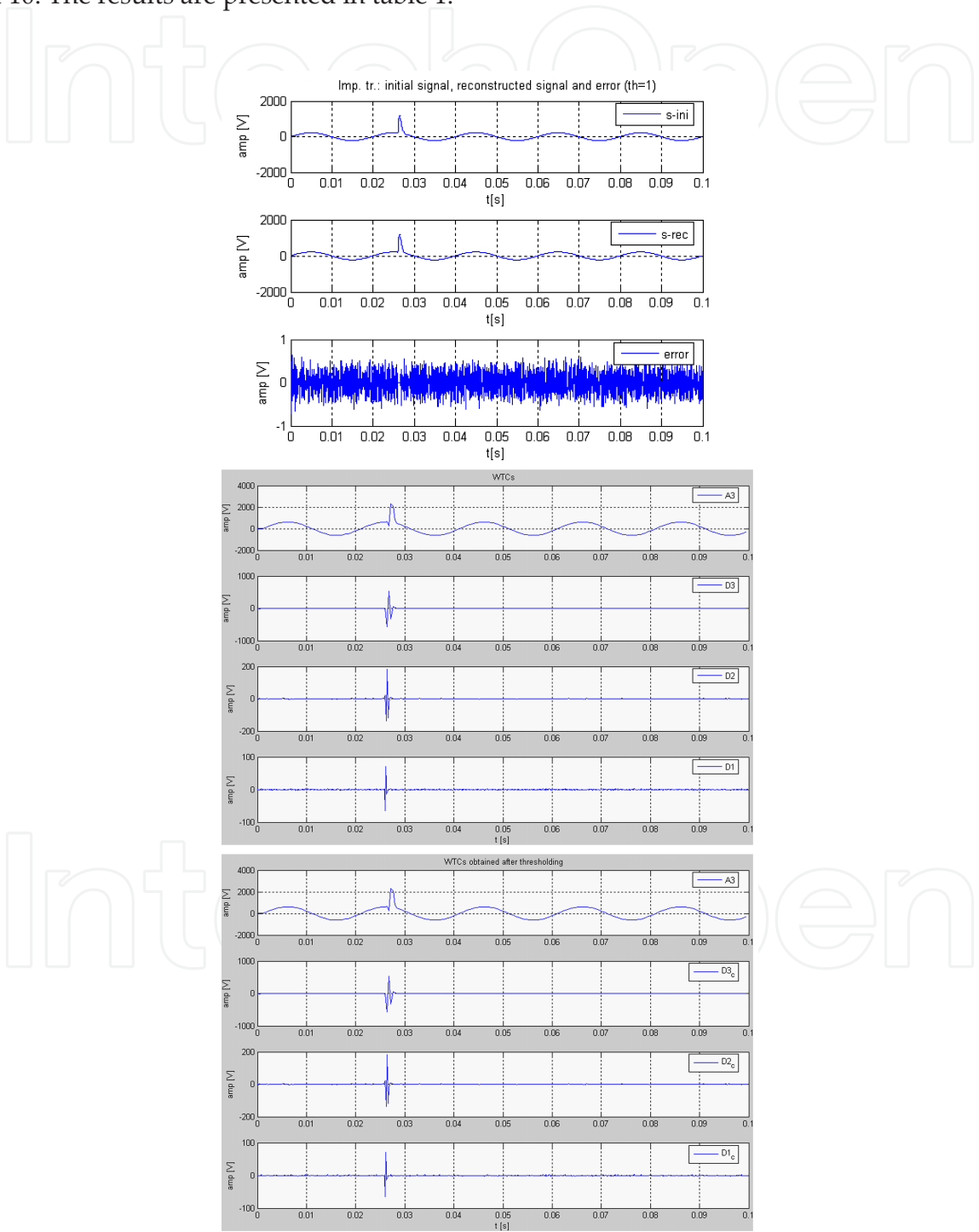


**Figure 3.** Impulsive transient compression with threshold value 1

| Signal | Ψ(t) | Levels | $\eta_s$ | NMSE [%] | CR |
|---|---|---|---|---|---|
| | Db3 | 3 | 1 | 5.5154e-006 | 1.47 |
| | Db3 | 3 | 5 | 2.7151e-005 | 6.54 |
| | Db3 | 3 | 7 | 2.7827e-005 | 7.09 |
| | Db3 | 3 | 10 | 2.6502e-005 | 7.14 |
| | Db3 | 4 | 5 | 2.9240e-005 | 10.7 |
| | Db3 | 4 | 7 | 3.1081e-005 | 11.17 |
| | Db3 | 4 | 10 | 3.1515e-005 | 11.7 |
| | Db3 | 5 | 5 | 3.6143e-005 | 9.66 |
| | Db3 | 5 | 7 | 4.0148e-005 | 12.42 |
| Impulsive transient | Db3 | 5 | 10 | 5.6165e-005 | 15.04 |
| | Db4 | 3 | 5 | 2.9386e-005 | 6.94 |
| | Db4 | 3 | 7 | 2.9246e-005 | 7.14 |
| | Db4 | 3 | 10 | 2.9481e-005 | 7.3 |
| | Db4 | 4 | 5 | 3.2845e-005 | 10.47 |
| | Db4 | 4 | 7 | 3.0742e-005 | 10.93 |
| | Db4 | 4 | 10 | 3.1029e-005 | 11.05 |
| | Db5 | 4 | 5 | 3.0875e-005 | 9.85 |
| | Db5 | 4 | 7 | 2.8626e-005 | 10.36 |
| | Db5 | 4 | 10 | 3.1029e-005 | 10.69 |

**Table 1.** Compression results for impulsive transient

The initial value of threshold is 1. The size of the WTCs obtained after thresholding using the relations (9) and (10) is reduced as follows (first line from table 1): the coefficient *D1* at scale 1 has 2*303=606 samples (303 samples nonzero and their temporal positions), the coefficient *D2* at scale 2 has 2*167=334 samples, the coefficient *D3* has 2*85=170 samples and the coefficient A3 has 250 samples. The compressed signal has 1360 samples and the initial test signal has 2000. The compression ratio is 2000/1360=1.47.

From table 1 can be observed that the highest compression rate is 15.04. This value is obtained for Daubechies scaling function of order 3 (*Db3*), 5 levels of decomposition and the threshold value of 10. The order of *NMSE* error is $10^{-6}$.

If the threshold value is greater than or equal to 5 (Fig. 4), the signal distortions start to rise especially in the area of the overlapped impulsive transient. The enlargement of threshold leads to more and more information discarded and NMSE grow up.
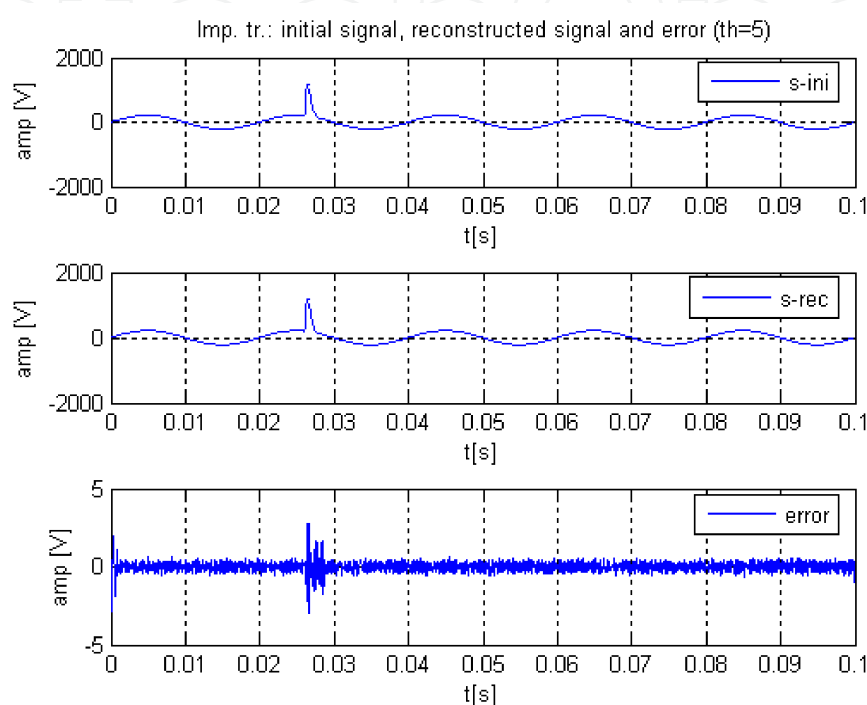
**Figure 4.** Impulsive transient compression with threshold value 5

Fig. 5 shows the second test signal, an oscillatory transient superimposed on a sinusoidal signal. The signal parameters and the decomposition parameters have the same values as the first test signal. The results are presented in table 2.

From table 2 the highest compression rate is 7.84. The value is lower than for the first test signal. This compression rate is obtained using the same settings: Daubechies scaling function of order 3 (*Db3*), 5 levels of decomposition and the threshold value of 10. The order of *NMSE* error is $10^{-5}$.

Again, if the threshold value is greater than or equal to 5 (Fig. 6), the signal distortions start to rise especially in the area of the overlapped oscillatory transient and NMSE grow up too.
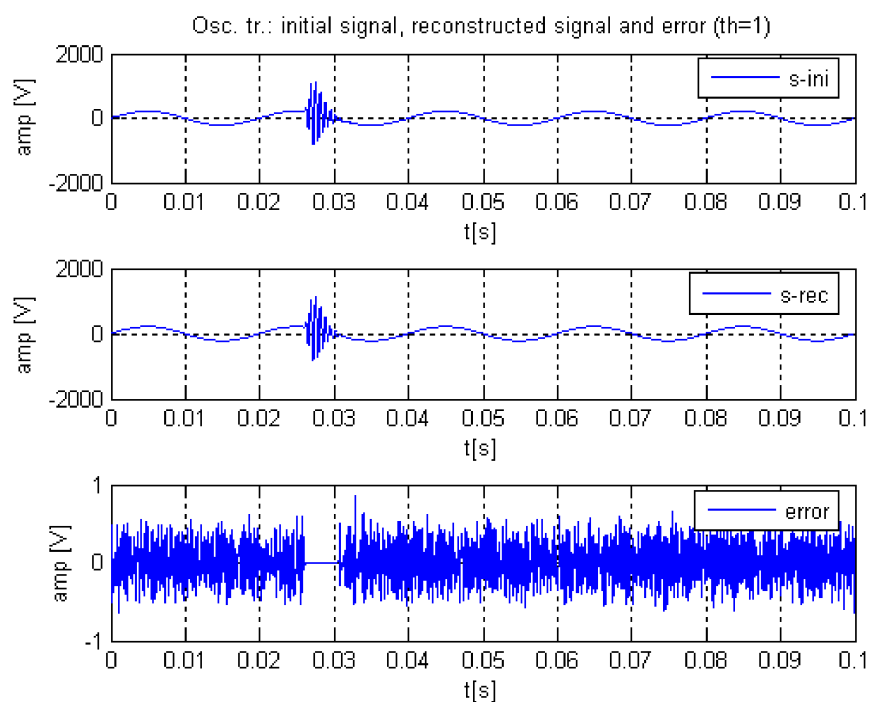
**Figure 5.** Oscillatory transient compression with threshold value 1

| Signal | Ψ(t) | Levels | η$_s$ | NMSE [%] | CR |
|---|---|---|---|---|---|
| | Db3 | 3 | 1 | 4.7257e-006 | 1.35 |
| | Db3 | 3 | 5 | 2.9394e-005 | 4.85 |
| | Db3 | 3 | 7 | 2.6282e-005 | 5.02 |
| | Db3 | 3 | 10 | 3.7811e-005 | 5.21 |
| | Db3 | 4 | 5 | 2.9285e-005 | 6.31 |
| | Db3 | 4 | 7 | 3.3209e-005 | 6.6 |
| | Db3 | 4 | 10 | 4.5275e-005 | 7.07 |
| | Db3 | 5 | 5 | 3.3699e-005 | 6.08 |
| | Db3 | 5 | 7 | 4.4197e-005 | 6.69 |
| Oscillatory transient | Db3 | 5 | 10 | 6.7879e-005 | 8.3 |
| | Db4 | 3 | 5 | 2.8067e-005 | 5.05 |
| | Db4 | 3 | 7 | 3.0176e-005 | 5.18 |
| | Db4 | 3 | 10 | 4.0081e-005 | 5.43 |
| | Db4 | 4 | 5 | 2.9924e-005 | 6.47 |
| | Db4 | 4 | 7 | 3,2733e-005 | 6.87 |
| | Db4 | 4 | 10 | 4.2280e-005 | 7.38 |
| | Db5 | 4 | 5 | 2,9223e-005 | 6.89 |
| | Db5 | 4 | 7 | 3.6702e-005 | 7.22 |
| | Db5 | 4 | 10 | 4.7778e-005 | 7.84 |

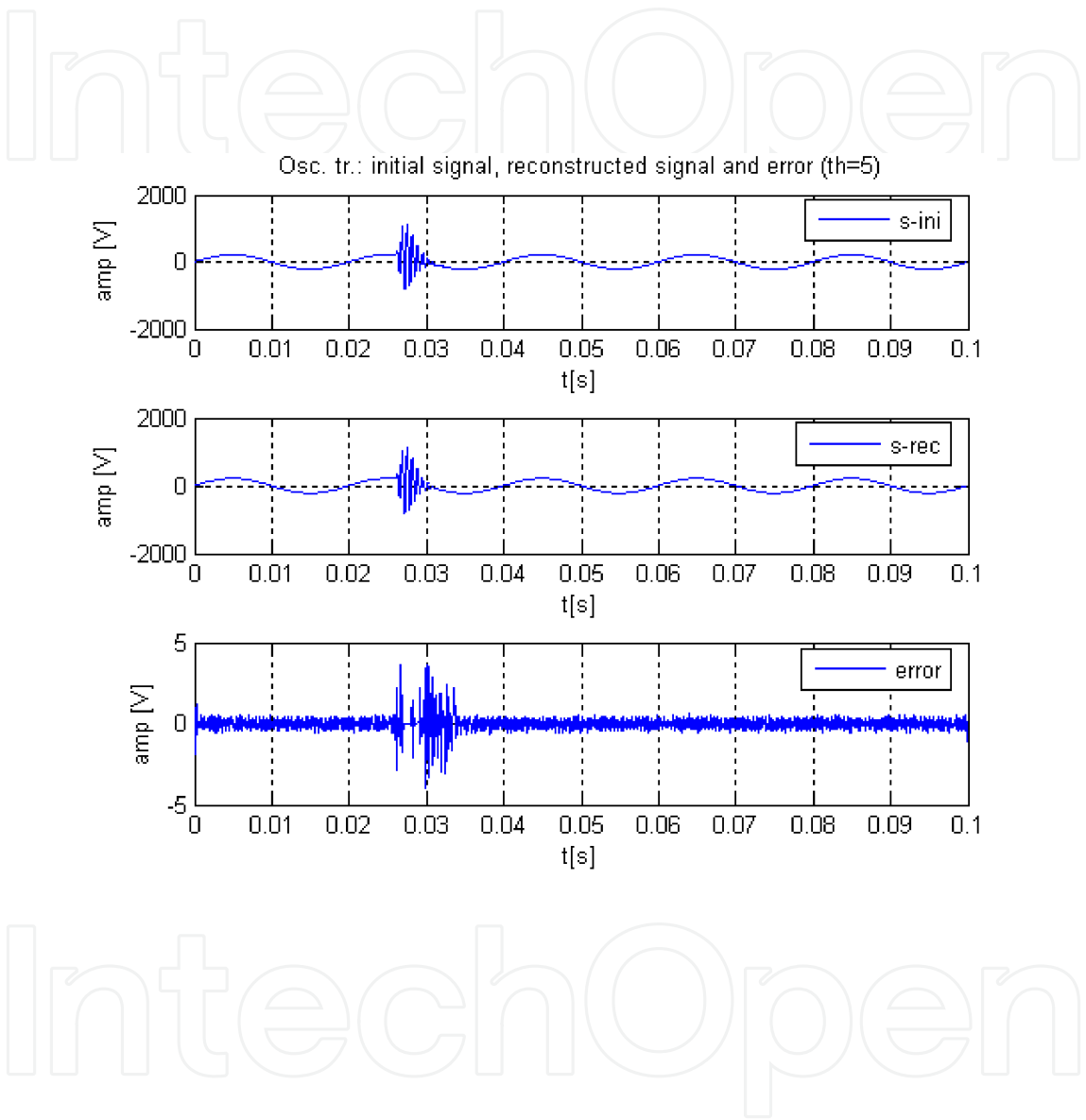**Table 2.** Compression results for oscillatory transient

**Figure 6.** Oscillatory transient compression with threshold value 5

### 2.2.2. Voltage swell

Fig. 7 shows the third test signal, a swell with magnitude of 375 V superimposed on a sinus-oidal signal. The rest of signal parameters and the decomposition parameters have the same values as the previous test signals. The results are presented in table 3.
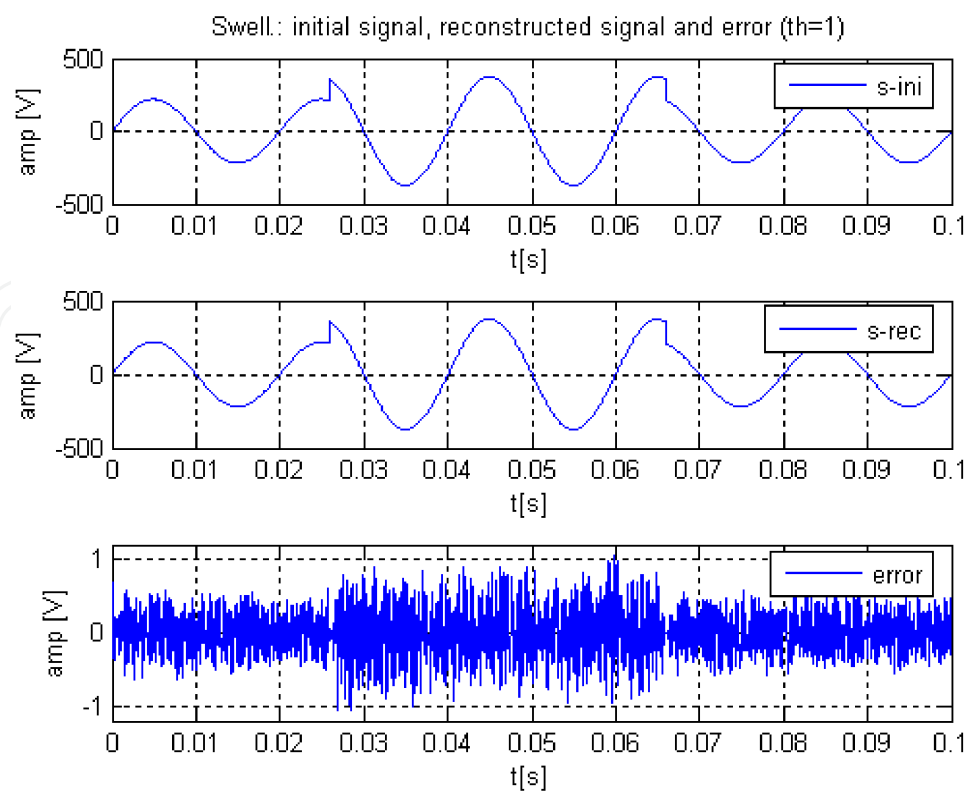
**Figure 7.** Voltage swell compression with threshold value 1

| Signal | $\Psi(t)$ | Levels | $\eta_s$ | NMSE [%] | CR |
|---|---|---|---|---|---|
| | Db3 | 3 | 1 | 3.6484e-006 | 1.21 |
| | Db3 | 3 | 5 | 3.3454e-005 | 6.9 |
| | Db3 | 3 | 7 | 3.4048e-005 | 7.14 |
| | Db3 | 3 | 10 | 3.5194e-005 | 7.19 |
| | Db3 | 4 | 5 | 3.7718e-005 | 10,47 |
| | Db3 | 4 | 7 | 4.0528e-005 | 11.17 |
| | Db3 | 4 | 10 | 4.1284e-005 | 11.7 |
| | Db3 | 5 | 5 | 3.7621e-005 | 9.05 |
| | Db3 | 5 | 7 | 4.4344e-005 | 10.47 |
| Voltage sag | Db3 | 5 | 10 | 5.8101e-005 | 13.42 |
| | Db4 | 3 | 5 | 3.4595e-005 | 6.62 |
| | Db4 | 3 | 7 | 3.2270e-005 | 6.99 |
| | Db4 | 3 | 10 | 3.5533e-005 | 7.14 |
| | Db4 | 4 | 5 | 3.8236e-006 | 9.3 |
| | Db4 | 4 | 7 | 6.4098e-006 | 10.47 |
| | Db4 | 4 | 10 | 3.9005e-005 | 10.81 |
| | Db5 | 4 | 5 | 3.7183e-005 | 9.13 |
| | Db5 | 4 | 7 | 3.9994e-0056 | 9.95 |
| | Db5 | 4 | 10 | 4.1631e-005 | 10.36 |

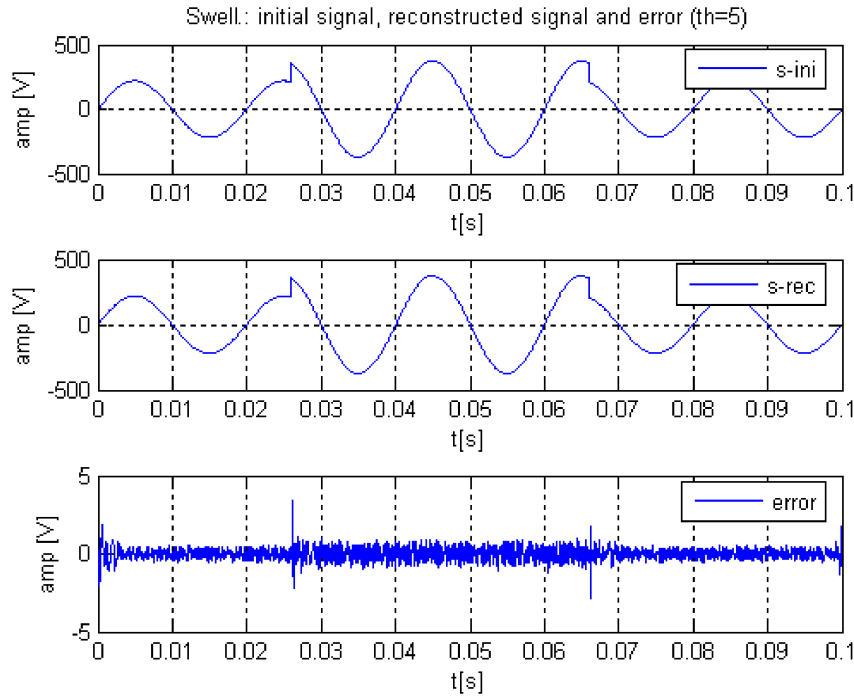**Table 3.** Compression results for swell

**Figure 8.** Volatge swell compression with threshold value 5

From table 3 the highest compression rate is 13.42. The value is higher than for the second test signal. This compression rate is obtained using the same settings as for previous test signals: Daubechies scaling function of order 3 (*Db3*), 5 levels of decomposition and the threshold value of 10. The order of *NMSE* error is $10^{-5}$.

Again, if the threshold value is greater than or equal to 5 (Fig. 8), the signal distortions start to rise especially in the area of the overlapped disturbance and NMSE grow up too.

A few conclusions are described below:

- using 5 levels of decomposition, Daubechies scaling function of order 3 (*Db3*) and 5 (*Db5*) is obtained the highest compression rate;

- for a higher threshold value the compression rate will be higher, but NMSE and signal distorsions grow up;

- for different types of disturbances using the same settings the compression rate is different.

### 2.3. New wavelet-based data compression technique using decimation and spline interpolation

This chapter describes a new technique proposed for signal compression based on wavelet decomposition and spline interpolation method (Găşpăresc, 2010). It follows to obtain a higher compression ratio than the general data compression method used for the test signals analysed before, where for a given signal it is applied a signal decomposition and than thresholding of WTCs $D_i$, *i=1,...,N*. Using this method the coefficient $A_N$ is not thresholded

and it has the largest number of samples from all the coefficients of signal decomposition. In order to obtain a higher sample rate this coefficient is decimated with a decimation factor *Fd* and at signal reconstruction will be interpolated. The cost is the increase of *NMSE* error.

Given an interval *[a,b]* and a divizion $\Delta$:$a=x_0<x_1<...<x_n=b$, a function *S : [a,b]→R* is called cubic spline interpolation function if this function meets the next conditions:

- *S* is a polynomial of degree at most 3 on any interval $(x_k,x_{k+1})$, *k=1,…,N* (relation 13);

- $S \epsilon C^2([a,b])$;

- $S(x_i)=f(x_i)$, $i\epsilon(0,1,..., n)$, where *f(x)* is the interpolated function.

$$S(x) = a_i + b_i x + c_i x^2 + d_i x^3, \forall x \in [x_{i-1}, x_i] \tag{13}$$

The proposed technique is tested using an impulsive transient with magnitude of 700 V superimposed on a sinusoidal signal (Fig. 9-10). The sampling rate is 5 MHz in this case. The signal is decomposed using a Daubechies scaling function of order 4 and 5 and respectively 4 levels of decomposition. Than the signal it is compressed using a threshold (Table 4).
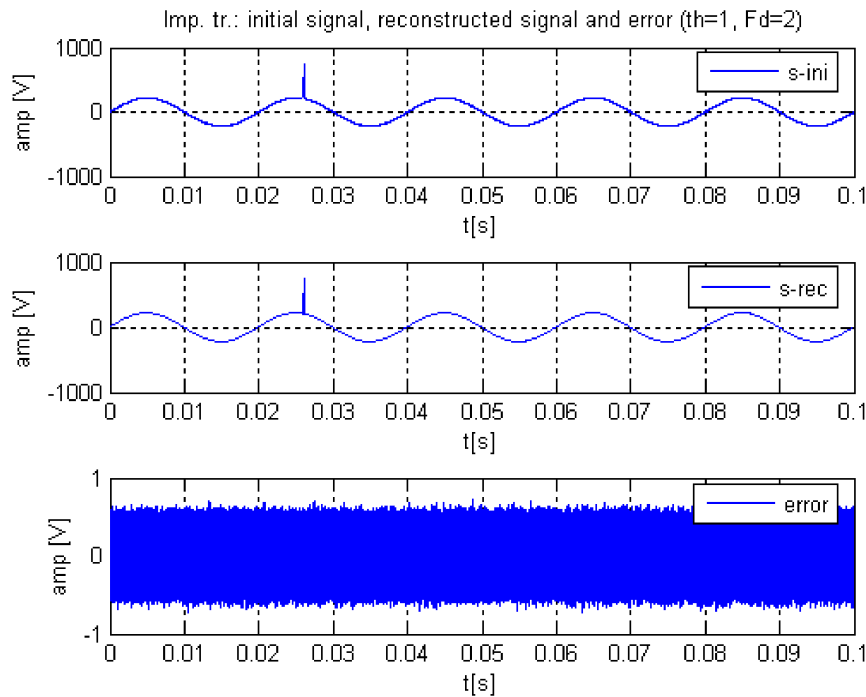


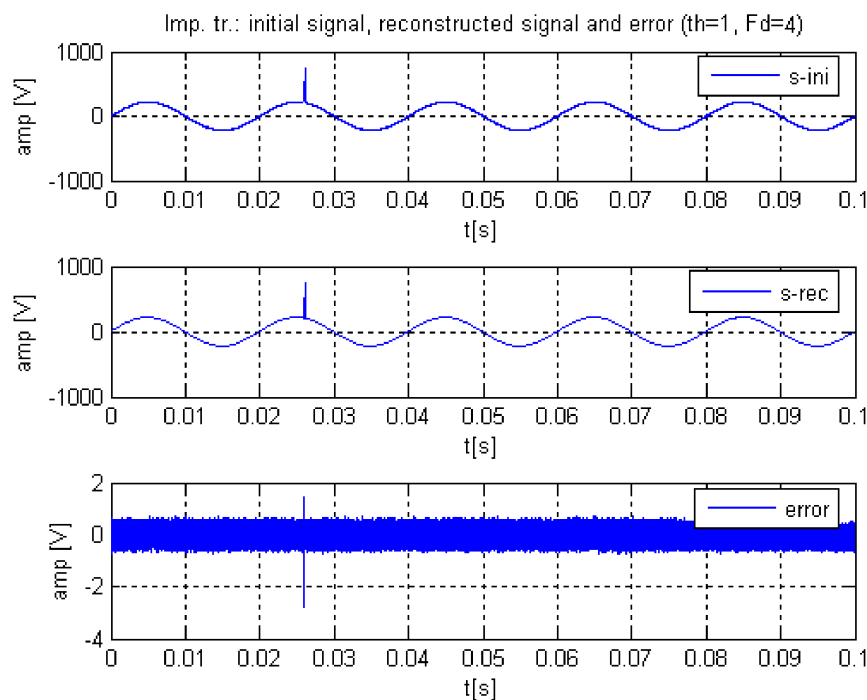**Figure 9.** Impulsive transient compression with decimation factor *Fd=2*

**Figure 10.** Impulsive transient compression with decimation factor *Fd=4*

| Signal | Ψ(t) | η$_s$ | Fd | NMSE [%] | CRa |
|---|---|---|---|---|---|
| | Db4 | 3 | 2 | 2.2901e-004 | 32 |
| | Db5 | 3 | 2 | 2.2901e-004 | 32 |
| Impulsive transient | Db4 | 3 | 4 | 9.8005e-004 | 63.99 |
| | Db5 | 3 | 4 | 2.2830e-004 | 63.98 |

**Table 4.** Compression results for impulsive transient using the proposed technique

From table 4 can be observed that the highest compression ratio is 63.99. This value is obtained for Daubechies scaling function of order 4 (*Db4*), 4 levels of decomposition, threshold value of 3 and the decimation factor value of 4. The order of *NMSE* error is 10$^{-4}$. The resulted compresion ratio is 4 times higher than the values from the prevoius tables, but the NMSE error is higher also.

This proposed technique is efficient especially for signals acquired at high sample rates, when are acquired a sufficient number of samples of the disturbance overlapped on the power supply signal. If this number is small, after the decimation of coefficient $A_N$ are losed disturbance details which cannot be reconstructed by interpolation and the reconstructed signal will contain distortions on the disturbance area.

## 3. Data compression using slantlet transform

### 3.1. Slantlet transform

The Slantlet transform (SLT) is a relatively new multiresolution technique base on DWT. In fact, it is an orthogonal DWT with two zero moments and compared to DWT provides better time localization (Selesnick, 1999), (Panda et al., 2002), (Duda, 2008).

In (Panda et al., 2002) is proposed a new approach for power quality data compression based on SLT. The technique is compared with the discrete cosine transform (DCT) and the discrete wavelet transform (DWT) using various types of power quality disturbances (impulse, sag, swell, harmonics, momentary interruption, oscillatory transient, voltage flicker).

In order to compare DWT and SLT is considered a two-scale iterated filterbank (Fig. 11) and a two-scale slantlet filterbank (Fig. 12). First three blocks from Fig. 12 are not products. The filters have shorter length and the difference grows with the number of stages. The time localization is improved but SLT filterbank is less frequency selective.
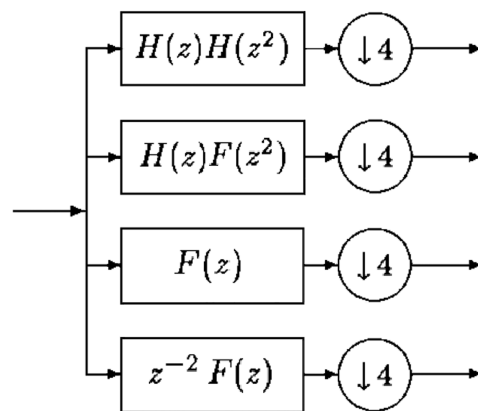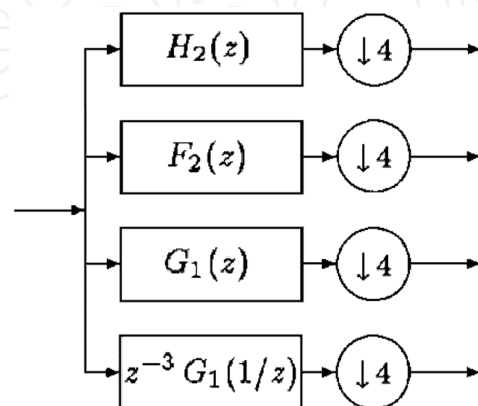


**Figure 11.** Two-scale iterated filterbank



**Figure 12.** Two-scale slantlet filterbank

The SLT is based on the principle of designing different filters for different scales unlike iterated filterbank approaches for DWT. In (Selesnick, 1999) are described the basis for filterbank design, polynomial expresions to determine the filter coefficients and an algorithm to calculate the transform.

The filter coefficients are

$$E_0(z) = G_1(z) = (-\frac{\sqrt{10}}{20} - \frac{\sqrt{2}}{4}) + (\frac{3\sqrt{10}}{20} + \frac{\sqrt{2}}{4})z^{-1} + \left(-\frac{3\sqrt{10}}{20} + \frac{\sqrt{2}}{4}\right)z^{-2}$$
$$+\left(\frac{\sqrt{10}}{20} - \frac{\sqrt{2}}{4}\right)z^{-3}$$

$$E_1(z) = F_2(z) = (\frac{7\sqrt{5}}{80} - \frac{3\sqrt{55}}{80}) + (-\frac{\sqrt{5}}{80} - \frac{\sqrt{55}}{80})z^{-1} + \left(-\frac{9\sqrt{5}}{80} + \frac{\sqrt{55}}{80}\right)z^{-2}$$
$$+\left(-\frac{17\sqrt{5}}{80} + \frac{3\sqrt{55}}{80}\right)z^{-3} + \left(\frac{17\sqrt{5}}{80} + \frac{3\sqrt{55}}{80}\right)z^{-4} + \left(\frac{9\sqrt{5}}{80} + \frac{\sqrt{55}}{80}\right)z^{-5}$$
$$+\left(\frac{\sqrt{5}}{80} - \frac{\sqrt{55}}{80}\right)z^{-6} + \left(-\frac{7\sqrt{5}}{80} - \frac{3\sqrt{55}}{80}\right)z^{-7}$$

$$E_2(z) = H_2(z) = (\frac{1}{16} + \frac{\sqrt{11}}{16}) + (\frac{3}{16} + \frac{\sqrt{11}}{16})z^{-1} + (\frac{5}{16} + \frac{\sqrt{11}}{16})z^{-2}$$
$$+(\frac{7}{16} + \frac{\sqrt{11}}{16})z^{-3} + (\frac{7}{16} - \frac{\sqrt{11}}{16})z^{-4} + (\frac{5}{16} - \frac{\sqrt{11}}{16})z^{-5}$$
$$+(\frac{3}{16} - \frac{\sqrt{11}}{16})z^{-6} + (\frac{1}{16} - \frac{\sqrt{11}}{16})z^{-7}$$

$$E_3(z) = z^{-3}E_2(\frac{1}{z})$$

$$(14)$$

Table 5 displays the test results obtained using DCT, DWT and SLT (Panda et al., 2002). The compression performance is analysed based on percentage of energy retained (relation 15) and mean square error (MSE) in decibels (relation 16). The compression rate is 10. The results shows improved values for energy retained (near 4%) and MSEs.

$$\left[\frac{\text{\textit{Vector} norm of the retained SLT coefficients after thresholding}}{\text{Vector norm of the original SLT coefficients}}\right] \times 100 \qquad (15)$$

$$MSE[dB] = 10 \left[ \log_{10}(\frac{1}{N} \sum_{i=1}^{N} \| x(i) - \hat{x}(i) \|^2) \right] \tag{16}$$

| Signal | Energy Retained [%] | | | MSE [dB] | | |
|---|---|---|---|---|---|---|
| | DCT | DWT | SLT | DCT | DWT | SLT |
| Impulse | 88.01 | 91.13 | 94.01 | -10.67 | -13.54 | -16.98 |
| Sag | 87.81 | 90.01 | 93.20 | -10.08 | -13.04 | -17.54 |
| Swell | 89.46 | 91.01 | 94.44 | -11.88 | -13.77 | -17.95 |
| Harmonics | 87.69 | 90.89 | 93.14 | -11.04 | -13.31 | -17.68 |
| Momentary Interruption | 90.44 | 91.10 | 94.11 | -12.27 | -15.89 | -18.79 |
| Oscillatory Transient | 91.63 | 90.88 | 95.04 | -12.98 | -14.45 | -19.07 |
| Voltage Flicker | 90.75 | 91.34 | 95.18 | -10.76 | -14.74 | -19.78 |

**Table 5.** Test results obtained using DCT, DWT and SLT (CR=10)

## 4. Conclusions

The research results on data compression using DWT presented in this work show the optimal order of Daubechies scaling function recommended in order to achieve the best compression ratio for three types of power quality disturbances and the necessary number of decomposition levels. An compression algorithm base on spline interpolation method that allows higher compression rates is also presented.

The Slantlet transform is analysed as a new approach for power quality data compression. The compression performance using SLT was compared based on percentage of energy retained and mean square error in decibels. The computer simulation tests using various power quality disturbances shows that SLT provides a more accurate reconstruction of the original signal than DCT and DWT.

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