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Adaptive Threshold for Electrical Disturbances Segmentation

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Abstract. The detection of the electrical signal discontinuities in the oscillographies recorded in substations and/or points of common coupling allows their segmentation, which is crucial for implementation of automated methods for detection, classification, location and storage by classes of disturbances in electric power systems. In this context, this study provides a way of determining an adaptive threshold that allows the segmentation of voltage or current signals based on Wavelets decomposition. The disturbances considered in this work were the short-duration voltage variations, impulsive and oscillatory transients, and harmonic distortions. The signals were synthetically generated. Moreover, white noise was added on the signals. Thus, a *Symlet* Wavelet was applied to the signals in order to denoise them. In the sequence, a *Daubechies* Wavelet was used to decompose the filtered signals. So, to determine the initial and final points of each segment, an adaptive threshold was established based on the energy and entropy of energy for the second level of decomposition. Thus, the number and position of each segment were determined according to the intersections of the detail curves and the thresholds found.

Keywords

Power Quality, Electrical Disturbances Segmentation, Adaptive Threshold, Wavelet Transform, Feature Extraction.

1. Introduction

Power Quality (PQ) in Electrical Power Systems (EPS) has become a matter of great concern both to the costumers and utilities. The main reason for this increase in interest is that PQ disturbances can have economic impacts on both. Power quality monitoring is the first step to identify sources of disturbances in a system to point out corrective actions. The importance and interest in PQ monitoring are growing, driven by constant efforts to improve PQ.

Any frequency variations or voltage waveform distortions can result in misoperation and/or failures of consumer's equipment, which can reduce their lifetime [1], [2].

In order to improve PQ, the source of disturbances should be identified before improvement actions [4]. Thus, to ensure a better PQ of a distribution power system, methods for automatic detection, classification, location and data storage became essential [1], [5]. In this sense, continuous data recording (with or without disturbances) are required, which leads to a huge volume of data to be inspected by experts [2], [3].

In general, Wavelet Transforms (WT) has been used for many years in such areas as image compression, mechanical vibrations and acoustic analysis [1]. Many studies on the use of WT in signal analysis have shown their ability to filter noise and for accurate detection of abrupt changes and discontinuities in electrical signals, as well as feature extraction [5]. This has led to its application in PQ disturbances identification.

The main reason for its success lies on the fact that the wavelet function is the time-frequency decomposition, which generates coefficients in different scales. This property supports the WT analysis of signals with transient response due to PQ disturbances present in voltage, current and/or frequency [6], [7].

The Wavelets family most suitable for the detection of disturbances is the *Daubechies*, the *Symlets* with 8 coefficients and De Meyer [8]. For many authors, *Daubechies* family of wavelets is appropriate for the detection of most classes of disturbances [8], [9].

In this scenario, the research in question is intended to determine an adaptive threshold that allows the segmentation of electrical signals through their decomposition by *Daubechies* Wavelets. So, short-duration voltage variations (i.e., sags, swells and interruptions), transients and harmonic distortions were synthetically generated. In order to obtain voltage waveforms closer to reality, Gaussian noise was convolved with these signals. Hence, a filtering step based on Symlets Wavelet family was applied to the voltage signals [9], [10].

The paper is organized in five sections. Section 2 presents the proposed methodology for signals segmentation. The segmentation results are presented in Section 3. Finally, Section 4 discusses the conclusions and final comments about the research carried out so far.

2. Methodology

For each of the examined disturbances (short-duration voltage variations, impulsive and oscillatory transients, and harmonic distortions) an adaptive threshold was calculated based on the energy and entropy of the energy so that it would fit and allow the segmentation of signals to identify the stretches that contain the mentioned disturbances.

Considering that, the energy is the quadratic sum for each component of each detail leaf decomposed, the percentage energy can be obtained by Equation 1.

$$E_T(\%) = Energy = \sum_{j=1}^{N} \left(E_j\right)^2 \times 100 \quad (1)$$

Then the percentage energy entropy for a given level of decomposition is given by Equation 2.

$$WEE = Entropy = -\sum_{j=1}^{N} \frac{E_j}{E_T} \log\left(\frac{E_j}{E_T}\right) \quad (2)$$

From the above equations, Equation 3 was empirically obtained, which determines the threshold used in the segmentation of voltage signals with the disturbances to be identified. Thus, the following equation was used to obtain the adaptive threshold value:

$$Threshold = \left| \frac{3}{5} \times \sqrt{E_T} \times WEE \right| \quad (3)$$

The percentage energy value and, consequently, the energy entropy value are directly related to the severity of a particular disturbance [11].

Based on this behaviour, the calculation of the adaptive threshold allows tracing the graph of Fig. 1, which illustrates this feature. In this figure, it is observed that the threshold value is maximized according to the increase of disturbance sag severity, which explains the need of an adaptive threshold.

Based on the severity of the events and definition of the adaptive threshold to each signal analysed, it was possible to observe the intersections between the defined threshold and the WT detail coefficients.

These intersections determine the initial and final end time points of the disturbances, such as illustrated by Fig. 2 and Fig. 4.

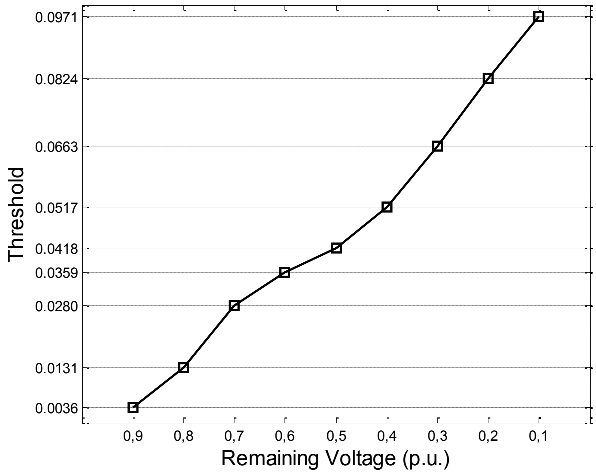

Fig. 1. Threshold value according to the severity of the sag.

As can be seen in Fig. 2, the initial (0.065 seconds) and final (0.13 seconds) time points of the sag are evident by *Daubechies* decomposition in the second detail level. The threshold (dashed line) calculated according to Equation 3, allows the segmentation of the signal by separating the voltage without disturbance and the manifested sag.

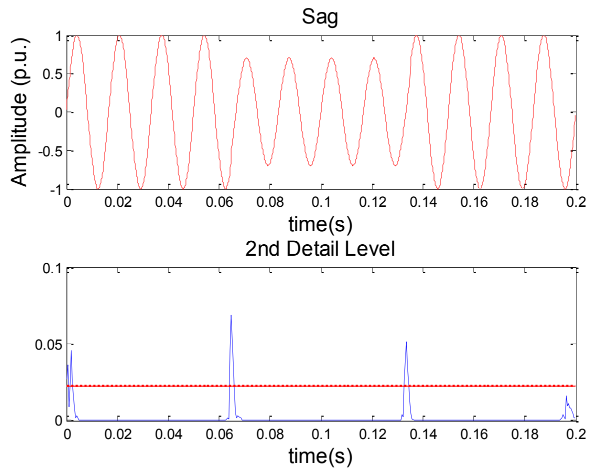

Fig. 2. Voltage waveform with sag and its adaptive threshold determined.

It is important to mention that for other disturbances examined in this study, it can also be observed that the energy and the entropy energy are directly related to their severity. [11].

Fig. 3 illustrates the threshold for a case with harmonic distortion. It can be observed that where the total harmonic distortion (THD) of the signal was more severe, the calculated threshold value was also higher. This characteristic also explains the need for an adaptive threshold.

From Fig. 4, the initial and final time points of the occurrence of harmonic distortion are highlighted using the second level of decomposition by *Daubechies* Wavelet family. Once a threshold (dashed line) was determined to intersect at such points (beginning at 0.065 seconds and ending at 0.13 seconds), the curve can be split to separate the segments without distortion from the segment affected by harmonic components.

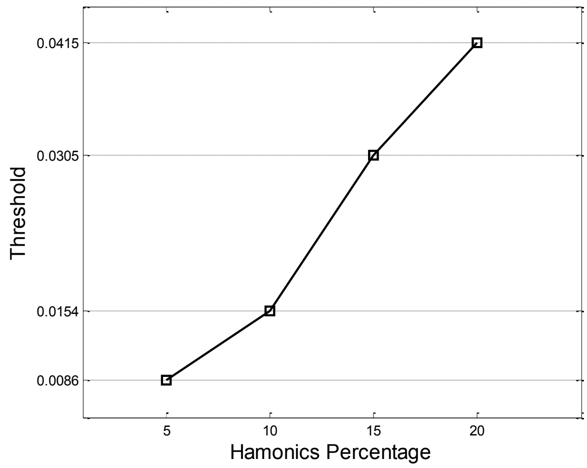

Fig. 3. Threshold value according to severity of the total harmonic distortion.

It is important to mention that, with the support of *Matlab*, the disturbances (voltage sags, swells, interruptions, transients and harmonic distortions) were generated as found in [9] and [10]. In these references, the disturbances appears in signals up to 0.2 seconds or 12 cycles with amplitudes between -1 and 1 p.u. related with the nominal voltage.

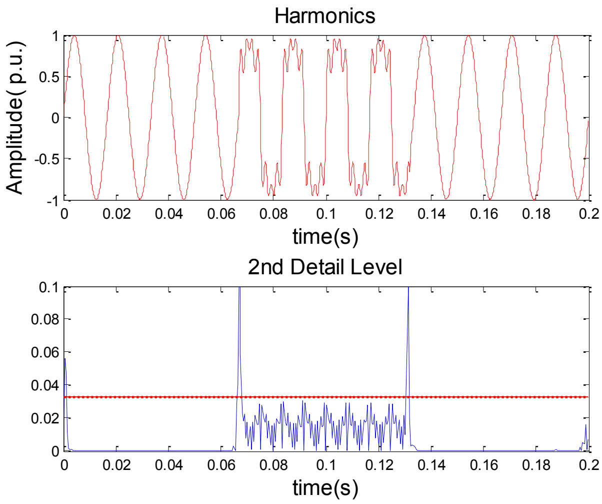

Fig. 4. Voltage waveform with harmonic distortion and its adaptive threshold determined.

In this research, the resulting signals were convolved with Gaussian noise, where prior denoising of the signals, through the Wavelets *Symlets*, was necessary. The *Symlets* were chosen because they had better results in this task than other families analyzed such as *Daubechies* and *Coiflets*.

For the task of segmentation of disturbances, the families *Daubechies*, *Coiflets* and *Symlets* were analyzed, because, a priori, there is no general rule that indicate which will be the best Wavelet to be used as well as the better level of decomposition.

To determine the behaviour of the adaptive threshold for each of these disturbances, the total length of the synthetic signals was considered (12 cycles), and the voltage amplitude values for each situation were analysed, respecting the indicated limits. This means for sags 0.1 to 0.9 p.u., swells from 1.1 to 1.8 p.u., oscillatory transients 2 p.u. to 9 p.u., and in case of harmonics, the third, fifth and seventh components were added to the signal respecting their percentage categories indicated in [12]. The sags, swells and interruptions disturbances were generated with 4 cycles of duration.

These signals were acquired using 64, 128 and 256 samples per cycle. The best results (adaptive thresholds with appropriate values) were found for signals represented by 128 samples per cycle.

The following section tables present the amplitudes of the disturbances, their values of the adaptive threshold, calculated according to Equation 3, and the number of the segments obtained for each disturbance considered in this research.

3. Results

A. Sags

In the case of voltage sags, nine levels of amplitude were analysed in order to verify the behaviour of the threshold, as can be seen in Table I.

For all cases analysed, the adaptive threshold found three segments, as this intersected the details curve in the start and end points of the disturbance. It is important to mention that the first and last half cycles are not considered because they do not represent real discontinuities in the signs. This can be illustrated by the second graph in Fig. 2 that represents the details curve to the second level of decomposition *Daubechies* 6.

The *Daubechies* Wavelet with 6 coefficients was chosen because it presented the best results (required lower levels of decomposition and showed prominent peaks indicating the discontinuities) in the segmentation task for the analysed voltage sags.

TABLE I. SAGS CHARACTERISTICS.

Sags		
Amplitude (p.u.)	***Adaptive Threshold***	***#Segments***
0.9	0.0036	3
0.8	0.0131	3
0.7	0.0280	3
0.6	0.0359	3
0.5	0.0418	3
0.4	0.0517	3
0.3	0.0663	3
0.2	0.0824	3
0.1	0.0971	3

B. *Swells*

The identification of the start and end points of swells disturbances has a similar behaviour to that of voltage sags. Decomposition by *Daubechies* Wavelets 6 was also used with two levels of decomposition. It was sufficient for the identification and subsequent segmentation of the analysed signal discontinuities.

The performance of the adaptive threshold found was evaluated for eight levels of intensity of disturbances, as it can be seen in Table II. This effectively indicated the start and end of voltage swells, through three segments. It is important to mention that the characteristics of duration and magnitude indicated in [12] were considered.

TABLE II. SWELLS CHARACTERISTICS.

Swells		
Amplitude (p.u.)	***Adaptive Threshold***	***#Segments***
1.1	0.0026	3
1.2	0.0098	3
1.3	0.0186	3
1.4	0.0251	3
1.5	0.0310	3
1.6	0.0352	3
1.7	0.0406	3
1.8	0.0486	3

Fig. 5 illustrates one of the cases analysed and segmented to the situation of increased tension. The first graph shows the disturbance duration of four cycles, and the second graph shows two intersections with the adaptive threshold. The first and last half cycles are not considered as mentioned previously, because their discontinuities indicate just the start and the end of the complete synthetic signals.

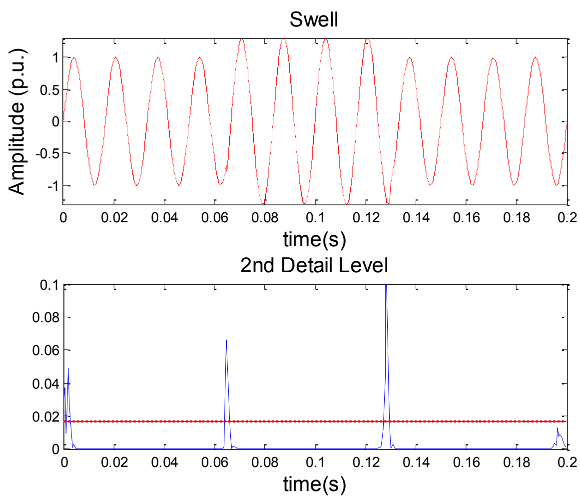

Fig. 5. Voltage waveform with swell and its adaptive threshold determined.

C. *Interruptions*

The voltage interruptions were also analysed according to the approach proposed in this work, i.e., aiming the identification of a threshold to determine the start and end of this disturbance.

Nine cases were tested according to the magnitude and duration indicated in [12]. It is important to say that all these results presented three segments, as it can be observed in Table III.

TABLE III. INTERRUPTIONS CHARACTERISTICS.

Interruptions		
Amplitude (p.u.)	***Adaptive Threshold***	***#Segments***
0	0.0962	3
0.01	0.0983	3
0.02	0.0986	3
0.03	0.0947	3
0.04	0.0955	3
0.05	0.0922	3
0.06	0.1044	3
0.07	0.1023	3
0.08	0.1016	3

Fig. 6 illustrates one of the nine cases analysed and segmented to the case of voltage interruption. The details graph intersections with the adaptive threshold are evident because of the minimum amplitude of the interruptions.

As in previous cases, the best result, which required lower levels of decomposition and showed prominent peaks indicating the discontinuities, was obtained through decomposition by *Daubechies* Wavelets 6 and appropriate threshold was calculated according to Equation 3.

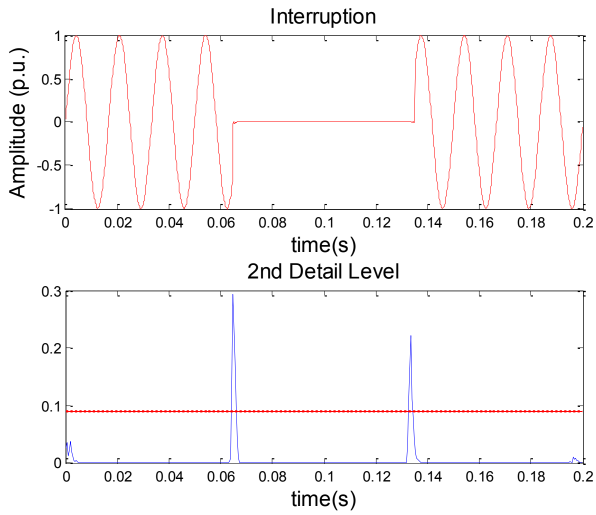

Fig. 6. Voltage waveform with interruption and its adaptive threshold determined.

D. *Oscillatory Transients*

In the case of the oscillatory transient, the time duration of the disturbance is shorter if compared to other analysed disturbances. It has about one cycle of duration. This led this disturbance to be identified and segmented by only one detail graph peak of the second level of Wavelets *Daubechies* 6 decomposition (Fig. 7).

Table IV shows the values of the thresholds calculated according to Equation 3 for the intensity levels of oscillatory transient as found in [12].

TABLE IV. OSCILLATORY TRANSIENTS CHARACTERISTICS.

Oscillatory Transients		
Amplitude (p.u.)	***Adaptive Threshold***	***#Segments***
2	0.2141	5
3	0.2951	7
4	0.3614	7
5	0.4132	5
6	0.4559	5
7	0.4928	7
8	0.5243	7
9	0.5526	7

In case of oscillatory transient there is a stretch of the disturbance details graph which presents certain oscillation, which makes the number of their intersections with the threshold greater than expected. This peculiarity creates more segments (5 or 7 segments) for this type of disturbance than that expected (3 segments).

The graph 2 of the Fig. 7 shows such higher number of intersections between the decomposed detail and the adaptive threshold.

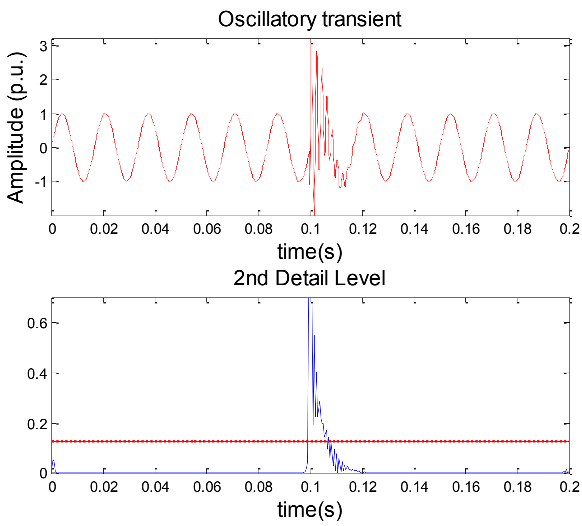

Fig. 7. Voltage waveform with oscilatory transient and its adaptive threshold determined.

E. *Impulsive Transients*

In impulsive transient, the time duration of the disturbance is very short, from nanoseconds to milliseconds according to [12]. Therefore, it is only the indication point of occurrence of the disturbance, as it can be seen in the second graph of Fig. 8, which had three segments as shown in Table V.

TABLE V. IMPULSIVE TRANSIENTS CHARACTERISTICS.

Impulsive Transients		
Duration	***Adaptive Threshold***	***#Segments***
< 50 ns	--	--
50 ns-1 ms	0.1402	3
> 1 ms	0.1889	3

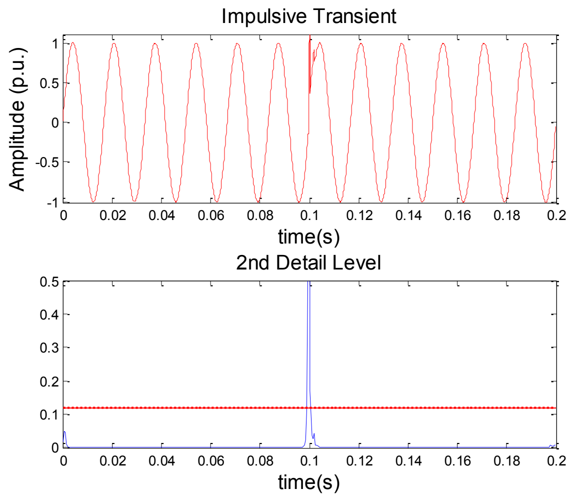

Fig. 8. Voltage waveform with impulsive transient and its example.

F. *Harmonic Distortions*

It may be noted in the second graph of Fig. 4 that the decomposition of signals contaminated by harmonics shows a clear change in behaviour during the occurrence of the disturbance. Equation 3, which determines the adaptive threshold value, allows to clearly identify the start and end of the disturbance (three segments), similar to the aforementioned disturbances. Table VI presents the number of segments in which the disturbance generated by the equations presented in [9], [10] was segmented.

TABLE VI. HARMONICS DISTORTIONS CHARACTERISTICS.

Harmonic Distortions		
DHT(%)	***Adaptive Threshold***	***#Segments***
5	0.0086	3
10	0.0154	3
15	0.0305	3
20	0.0415	3

It is important to highlight that in case of harmonic distortions, the research considered just the third, fifth and seventh harmonic components and the combination of them generates the DHT percentages presented in Table VI.

4. Conclusions

This research proposes a method of determining adaptive thresholds for segmentation of PQ signals. The method is based on the energy and entropy of energy from Wavelet decomposition. So, *Daubechies*, *Coiflets* and *Symlets* Wavelet families were evaluated for decomposing these signals.

The results that required lower levels of decomposition and had most prominent peaks in the discontinuities of the signals under analysis were obtained by *Daubechies* Wavelet with 6 coefficients.

Consequently, based on the calculation of adaptive thresholds, the number and location of each segment were determined. Thereby, the results previously found, show that the calculation of the adaptive threshold is easily implement for power quality meters and presents good results in the presence of formulated synthetic signals.

The next steps of the research will treat signals generate by more specific software, such as ATP (Alternative Transients Program) and with real data recorded by PQ meters.

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