Failure Analysis in Power System by the Discrete Wavelet Transform

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Abstract: - Voltage variations are the most common power quality events that may result in corruption of different industrial processes. The electric power utility industry requires significant improvement in the quality of power provided to customers during faults or wide area system disturbance. Power system failure signals are monitored by using embedded systems. This paper presents an approach to provide the detection and location in time as well as the identification of power quality problems which are represented in both transient and fixed signals. The method was applied by using the discrete wavelet transform (DWT). The given signal is decomposed with wavelet transform and any change on the lower frequencies of the signal is detected at the finer wavelet transform resolution levels. The entropy contents of the signal are considered and a relationship between this entropy contents and the one of the corresponding component is accomplished. This paper shows wavelet transform can be used to reduce data set while covering original information. Because of the reduced data set embedded systems can work within a wider time range. Paper helps power system analysis and classifies power system failures.

Key-Words: - Discrete wavelet transform, wavelet entropy, power system failure

1 Introduction

Power system quality includes problems caused by voltage sags, voltage swell and supply switching caused by autoreclose. All these faults are generally transitory, i.e., of a short term duration [1]. In general it is required that, they could be detected and identified. Nevertheless, whenever the disturbance which observe the waveform for a few cycles may not be enough to enable, there is a problem in this signal and complexity is to identify this problem [2, 3].

Electric power quality is an important issue in power systems nowadays. The demand for clean power has been increasing in the past several years. It is a well known fact in the signal processing area that the Fourier Transform is a powerful tool for the analysis of periodic information. The drawback is that its coefficients do not have inherent time information [1]. In other words, Fourier transform gives only frequency information about the signal. Therefore, it is difficult to observe individual events that occur at any time. Consequently, Fourier transform is not an ideal transform for nonstationary signals such as transient events. This problem is solved by applying wavelet transform.

Basis functions of a fast Fourier transform is sinusoids but small waves, called wavelet are used for wavelet transforms. Fast Fourier transform gives only frequency information but wavelet gives frequency and temporal information. Fourier analysis doesn't work well on discontinuous, "bursty" data. As shown above power system failure occurs within a very short period of time so it is bursty data. Thus, wavelet analysis can be used to describe power system failure.

Wavelet transform, which was discovered by the mathematicians at first, is a transform technique. It is possible to calculate low frequency and high frequency components of a given signal with wavelet transform. The analysis of the signals that its frequency contents vary with respect to time can be done somehow to sensitive by using this method. The wavelet transform can be applied to wide areas such as applied mathematics, signal processing, mechanical signal processing, biomedical signals etc. Additionally, wavelets are functions used to approximate other functions or data. They are particulary effective in approximating functions with discontinuites or sharp changes. The DWT corresponds to a filter bank iterated a finite number of times along the lowpass channel. One of its very important properties is the ability of the filter bank to represent polynomials, which is equivalent to the number of vanishing moments of the wavelet.

For power systems monitoring, embedded systems are used to capture data (instantaneous three phase voltage and current) and these systems can also be used for power system protection and communication. For future analysis these data could be used to understand failure reason within the use of wavelet analysis less data can be stored these embedded systems or using wavelet coefficients system classify failure type and protect systems.

There are several researches on increasing power quality in power systems. Some of these researches are summarized as follows. Wang et al proposed wavelet transform for the detection and identification of fluctuations in power sytem [4]. Li et al investigated the use of wavelet network to detect and to analyze disturbances [5]. The basic unit of the architecture is the wavelet network which combines the skill of the wavelet transform of analyzing non stationary signals with the classification capability of artificial neural networks. Kaewarsa and Attaitmongcol proposed further alternatives for power quantification based on wavelet neural networks [6]. An effective algorithm on online processing for analysis of power system with the application of signal processing techniques has been presented by Pardeshi et al [7].

The aim of this paper is to show an approach using MATLAB for which is proposed to adopt, not only to detect power quality problems but also to classify them. It is organized as follows: In Section 2, the power transients are presented. In Section 3, we discuss the DWT. Results on power system failure are also presented. The energy levels of the failure signals and the reconstructed signals are given. This is represented in Section 4.

2 Power Transients

Power quality is an issue that is becoming increasingly important to electricity consumers at all levels of usage. Sensitive equipment and non-linear loads are commonplace in both the industrial and the domestic environment. Therefore, several power system faults appear such as in the systems of electricity companies and end-users. The typical encountered faults are auto reclose, voltage sags and voltage swells. Definition of these faults is as follows [8].

An auto reclose is defined as a reduction in the supply voltage, or load current, to a level less than 0.1 p.u. for a time of not more than 1 minute. Interruptions can be caused by system faults, system equipment failures or control and protection malfunctions.

A voltage sag is a reduction in the rms voltage in the range of 0.1 to 0.9 p.u. for duration greater than half a mains cycle and less than 1 minute.

If an increasing change in the rms voltage in the range of 1.1 to 1.8 p.u. for a duration greater than half a mains cycle and less than 1 minute will happen, a voltage swell occurs. Especially, it is caused by system faults, load switching and capacitor switching. The identified faults are shown in Figure 1.

3 The Discrete Wavelet Transform

In recent years, wavelet transform is considered to be an efficient tool in digital signal processing. One of the main reasons for this is the easy computation, using the DWT which only requires a number of operations proportional to the size of the initial discrete data.

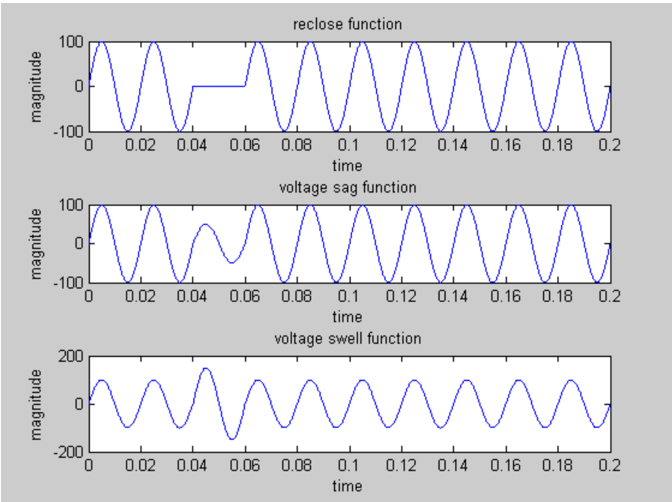

Fig. 1. Example of reclose, voltage sag and voltage swell functions in a power system

Most of the data which represent the physical problems does not include always random information but has an exact correlation structure.

The correlation is local in time and frequency. Frequently, these data sets will approximate with building blocks so that it could provide to localization in both time and frequency. Such building blocks will be able to detect the actual correlation structure from the data.

There are several advantages of the wavelet transform. Some of these are presented as follows: Wavelet series converge uniformly for all continuous functions, while Fourier series do not. Wavelet has the orthogonal bases that are continuous and independent from the problem. They are adjustable and adaptable. Wavelet decomposes and reconstructs functions actively using the multiresolution analysis. The DWT with the multiresoltion analysis easily converts the fuction to its coefficients because of the reversibility property. Additionally, the production of wavelets and the calculation of the DWT are well done with digital computers.

Wavelet is a mathematical function used to divide continuous time signal into different scale components. Each scale component can then be studied with a resolution that matches its scale. A wavelet transform is the representation of a function by wavelets. Therefore, the wavelet transform has demonstrated to be very useful and efficient transform for analyzing signals in different areas [9, 10]. The DWT uses analyzing wavelet functions, which are localized in both time and frequency to detect a small change in the input signals.

Any signal which can be generated with a set of expansion function in $L^2(R)$ is represented by

$$f(t) = \sum_{j,k} d_{j,k} 2^{j/2} \psi(2^j t - k) = \sum_{j,k} d_{j,k} \psi_{j,k}(t) \quad (1)$$

where the set of coefficients, $d_{j,k}$, is called the DWT of f(t) and $\psi_{j,k}(t)$ is a wavelet function [11]. If the $\psi_{j,k}(t)$ is constituted by an orthonormal basis for the signal, the $d_{j,k}$'s can be calculated using inner products as

$$f(t) = \sum_{j,k} \langle \psi_{j,k}(t), f(t) \rangle \, \psi_{j,k}(t) \quad (2)$$

From multiresolution analysis, scaling function which is constituted by the duality property of the DWT satisfies

$$\phi(t) = 2 \sum_{k=-\infty}^{\infty} h(k) \phi(2t - k) \quad (3)$$

for $k \in \mathbb{Z}$, where $\phi(t)$ is the scaling function and h(k) is the scaling function coefficients. Similarly, every orthogonal wavelet function must be expressed as a linear combination of scaling functions at the next finer scale and it can be arranged in another form related with the scaling function. This form of the wavelet function is defined by

$$\psi(t) = 2 \sum_{k=-\infty}^{\infty} g(k) \phi(2t - k) \quad (4)$$

$k \in \mathbb{Z}$, where $\psi(t)$ is the scaling function and g(k) is the wavelet function coefficients. This relation involves the equivalent conditions that

$$\sum_{k=-\infty}^{\infty} g(k) = 0 \quad (5)$$

and

$$\int \psi(t)\, dt = 0 \quad (6)$$

As a result of these conditions, the scaling function $\phi_{j,k}(t)$ have unity norm. $\phi_{j,k}(t)$ and $\psi_{j,k}(t)$ are orthogonal for all $j, k \in \mathbb{Z}$. This reveals the following conditions for the coefficients.

$$g(k) = (-1)^k h(1 - k) \quad (7)$$

$$\sum_{k=-\infty}^{\infty} h(k) g(k - 2n) = 0 \quad (8)$$

Assume that the signal has N samples so the DWT analysis produces N/2 samples at level one. N/4 samples at level two, N/8 samples at level three, similarly at N/2(k+1) samples at level k. As shown Figure 1 approximation coefficients decrease while decomposition level increases. These approximation coefficients will be used for signal analysis and reconstruction. But system looses signal information, so signal analysis, signal energy and entropy should be considered to decide which level is more suitable for analysis.

Previously mentioned, wavelets can be realized with good localization in time and frequency. Some wavelets are compactly supported, meaning exactly local in time (such as Daubechies and biorthogonal wavelets) or completely local in frequency. Time localization requires that most of the energy of a wavelet is gathered to a finite interval. In general, fast decay away from the center of the function is demanded. As for the frequency domain, there is a band limit for the frequency localization. The decay in high frequencies is related to the smoothness of the wavelets. The decay in low frequencies is related to the number of vanishing moments of the wavelet.

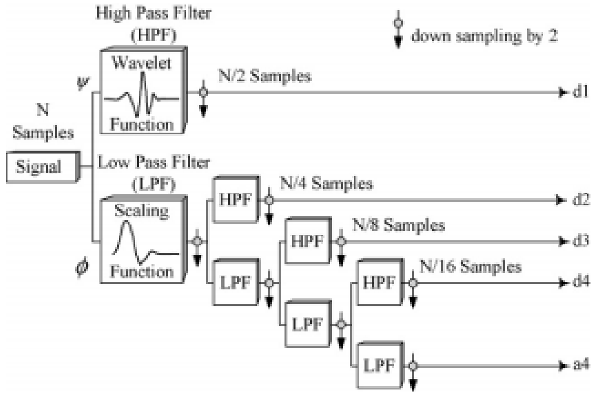

Fig. 2. The schmetical representation of the DWT

The large flexibility in the choice of the wavelet, allows the user to obtain optimal wavelet in specific applications. Since compactly supported wavelets are obtained by processing a finite sequence of numbers, the best efficient wavelet can be optimized for applications.

In this paper, the DWT is applied to data and Daubechies 4 (DB4), Daubechies 10 (DB10), Bior 3.7 (BIOR3.7) mother wavelets are used for comparison. The choosing factor of the Daubechies and biorthogonal wavelet functions is fast decay and having high frequency components. These wavelet functions are illustrated in Figure 3.

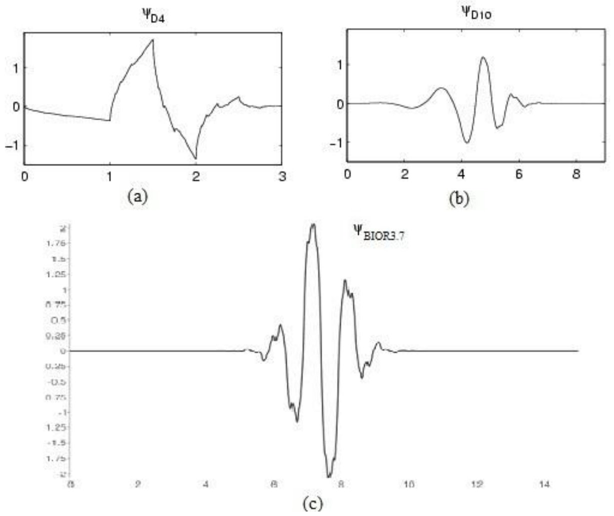

Fig. 3. Three mother wavelet used in analysis; (a) DB4, (b) DB10, (c) BIOR3.7 [12, 13]

All analysis is implemented on MATLAB. “Wavedec” command which performs a multilevel one-dimensional the discrete wavelet analysis is utilized and additionally “wenergy” command is applied to determine energy level of different levels.

4 Results

In this paper, a norm entropy-based effective feature extraction method that reduces the size of the feature vector from the wavelet decomposition and multiresolution analysis is proposed [14]. Three signal (auto reclose, voltage sag voltage swell) entropy levels are examined by using DB4, DB10, BIOR3.7 wavelets. Figure 4, 5 and 6 show entropy levels of reclose voltage sag and swell for DB4, DB10 and BIOR3.7 wavelet respectively.

In Figure 4, reclose signal is analyzed by using DB4, DB10 and BIOR3.7 wavelets. Ten level decomposition is applied and entropy level is showed. It can be clearly that after level 6 entropy level dramatically decreases. At the first 5 level decomposition, entropy level is around 99% so it is possible to obtain good reconstruction until level 6. In this work even 95% reconstruction is suitable to analyze failure signal. If level 6 entropy level is compared to, DB4, DB10 and BIOR3.7 wavelets, it is obvious that DB10 wavelet gives better results for reclose signal.

In Figure 5, the voltage sag signal is analyzed by using DB4, DB10 and BIOR3.7 wavelets. Ten level decomposition is applied and entropy level is showed. It can be clearly that after level 6 entropy level dramatically decreases. At the first 5 level decomposition, entropy level is around 99% so it is possible to obtain good reconstruction until level 6. In this work even 95% reconstruction is suitable to analyze failure signal. If level 6 entropy level is compared to DB4 and BIOR3.7 wavelets, it is obvious that DB10 wavelet gives better results for voltage sag signal.

In Figure 6, the voltage swell signal is analyzed by using DB4, DB10 and BIOR3.7 wavelets. Ten level decomposition is applied and entropy level is showed. It can be clearly that after level 6 entropy level dramatically decreases. At the first 5 level decomposition, entropy level is around 99% so it is possible to obtain good reconstruction until level 6. In this study, even 95% reconstruction is suitable to analyze failure signal. If level 6 entropy level is compared to DB4 and BIOR3.7 wavelets, it is obvious that DB10 gives better result for voltage swell.

Energy levels for DB4, DB10 and BIOR3.7 wavelets are examined to check correlation. Figure 8 shows energy levels of reclose, voltage sag and voltage sweel signals by using DB10 wavelet decomposition. Until level six, decomposition covers 95% of total energy so Figure 8 shows good correlation with Figure 4b, 5b and 6b. When same analysis is applied on the signal, it is obtained similar results for DB4 and BIOR3.7 wavelets. This results are shown in Figure 7 and Figure 9.

After the wavelet analysis of the signal from taken the power system, analysed signal is reconstructed. Reconstruction procedure is applied to signals by using DB4, DB10 and BIOR3.7 wavelet functions. Reconstructed signals can be compared with Figure 1. Figure 10, 11 and 12 show the reconstruction signals of voltage sag for DB4, DB10 and BIOR3.7 wavelets, respectively. Figure 13, 14 and 15 show again the reconstruction signals of voltage swell for DB4, DB10 and BIOR3.7 wavelets, respectively. Similarly, Figure 16, 17 and 18 show the reconstruction signals of reclose signal for DB4, DB10 and BIOR3.7 wavelets, respectively.

The original voltage sag, swell and reclose signals are given at Figure 1. In Figure 10, Figure 13 and Figure 16, DB4 is used for reconstruction of failure analysis. In Figure 11, Figure 14 and Figure 17, DB10 is used for reconstruction of failure analysis. In Figure 12, Figure 15 and Figure 18, BIOR3.7 is used for reconstruction of failure analysis. At Figure 11, the reconstructed voltage sag signal for DB10 wavelet is shown. It is selected to analyze from all the reconstructed signals for making a generilazition. But as expected from entropy and energy levels of decomposed signals also shown at Figure 5b and 8, after level six reconstructed signal shape is distorted.

At Figure 14, the reconstructed voltage swell signal is shown for DB10 wavelet. But as expected from entropy and energy levels of decomposed signals similarly shown at Figure 6b and 8, after level six reconstructed signal shape is distorted.

At Figure 17, the reconstructed reclose signal is shown. But as expected from entropy and energy levels of decomposed signals also shown at Figure 4b and 8, after level six reconstructed signal shape is distorted.

As easily can see from Figure 10, 11, 12, 13, 14, 15, 16, 17 abd 18, there is a good reconstruction until level six. Also it is easy to recognize good correlation exist beetween signal energy level of wavelet coefficients and its entropy level.

Table 1 summarizes energy levels of failure signals taken form the power system at different level decomposition by using different wavelet functions.

As seen from the table, level six can be chosen for good approximation and the energy level is around 95%, so level six is a good compromise. Also it is obvious that for reclose and voltage sag signals, BIOR3.7 wavelet has the best performance with respect to DB10 and DB4 wavelets. But for the voltage swell signal BIOR3.7 wavelet has better performance. Assume that original function has n elements after level six decomposition system will have n/64 elements. It means 1.5% less data.

5 Conclusion

Power system disturbances may not be periodic and may contain abrupt changes and impulse components. Fourier transform is not a very good tool for analyzing such signal transients. A new technique, the wavelet transform, is useful to determine signal transient in power systems. Therefore, the wavelet theory and its connections are fairly new concepts in power system applications.

In this paper, the DWT is applied to detect faults in power system. We provided three examples of wavelet functions applied to power system disturbances. We proposed to decompose the original fault signal into the smoothed and detailed version with the wavelet coefficients using the multiresolution analysis. Then we selected the wavelet coeffients including high energy components. All implementation was realized in MATLAB and we have also demonstrated that the DWT is a good tool for power system signal analysis, since mother wavelet and decomposition level should be selected properly.

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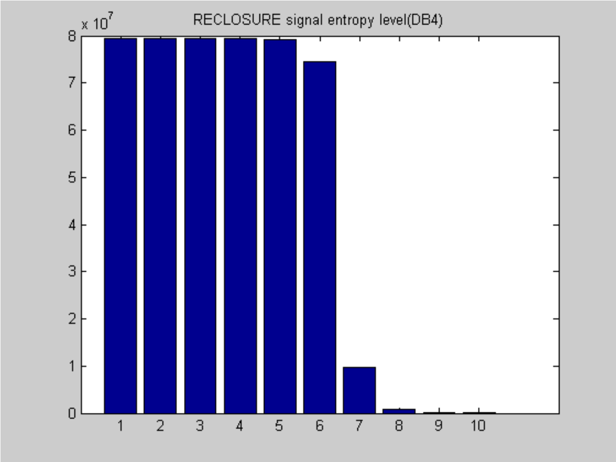
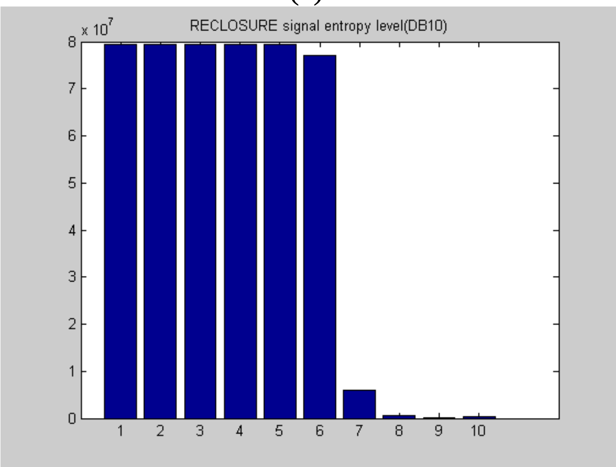
	level	Approximation Coefficent Numbers	Energy Level of Reclose	Energy Level of Voltage Sag	Energy Level of Voltage Sweel
DB4	1	n/2	100	100	100
	2	n/4	99,9994	99,9996	99,9996
	3	n/8	99,995	99,9953	99,9962
	4	n/16	99,9787	99,983	99,986
	5	n/32	99,8516	99,8824	99,8892
	6	n/64	94,3654	94,2285	94,0155
	7	n/128	16,355	14,7542	18,0271
	8	n/256	2,9081	1,911	1,7346
	9	n/512	2,4248	2,4264	2,4305
	10	n/1024	4,5304	4,3764	3,6087
DB10	1	n/2	100	100	100
	2	n/4	99,9995	99,9996	99,9996
	3	n/8	99,9967	99,9972	99,9977
	4	n/16	99,8455	99,8523	99,8781
	5	n/32	99,4564	99,5034	99,5892
	6	n/64	97,5112	98,2334	98,4295
	7	n/128	17,0641	14,78	11,8379
	8	n/256	15,5946	15,2934	13,853
	9	n/512	25,6765	25,6363	23,4802
	10	n/1024	40,013	40,0668	37,4207
BIOR3.7	1	n/2	100	100	100
	2	n/4	99,9997	99,9998	99,9998
	3	n/8	99,9834	99,9844	99,9872
	4	n/16	99,8084	99,8168	99,8495
	5	n/32	99,7043	99,7275	99,7645
	6	n/64	98,6991	98,9086	99,0091
	7	n/128	50,9491	49,5752	53,2822
	8	n/256	9,1865	6,6763	7,4364
	9	n/512	2,8153	3,3375	5,0603
	10	n/1024	5,2855	5,1985	4,2044

Table 1. Energy level of failure signals at different level decomposition by using different wavelet functions



(a)



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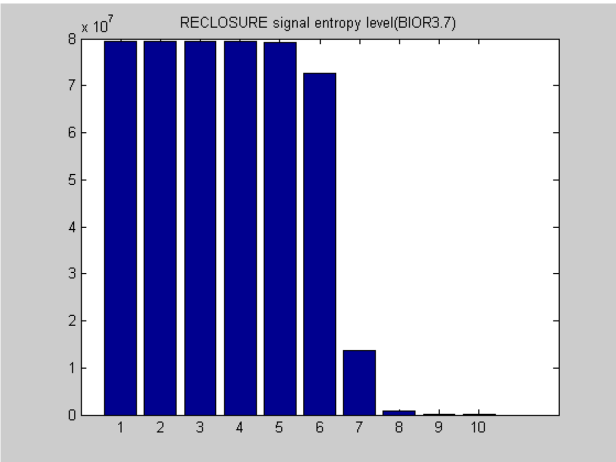
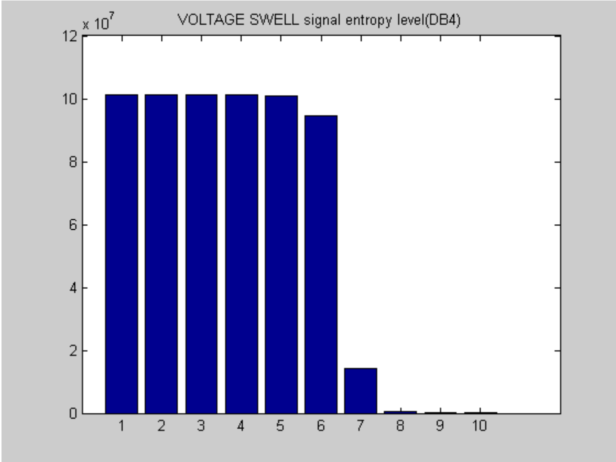


(c)

Fig. 4. Reclose signal entropy levels (a) for DB4 wavelet up to level ten decomposition, (b) for DB10 wavelet up to level ten decomposition, (c) for BIOR3.7 wavelet up to level ten decomposition



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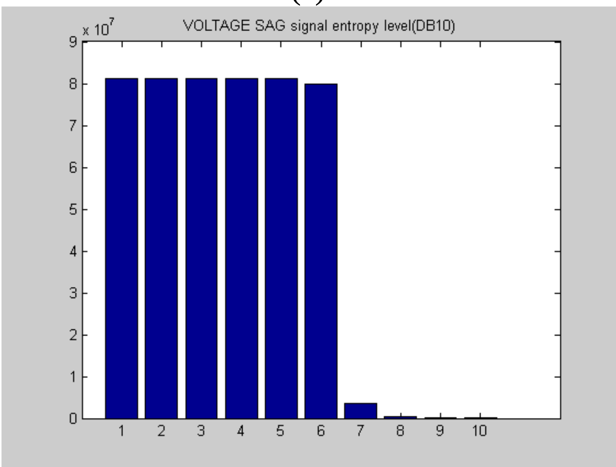

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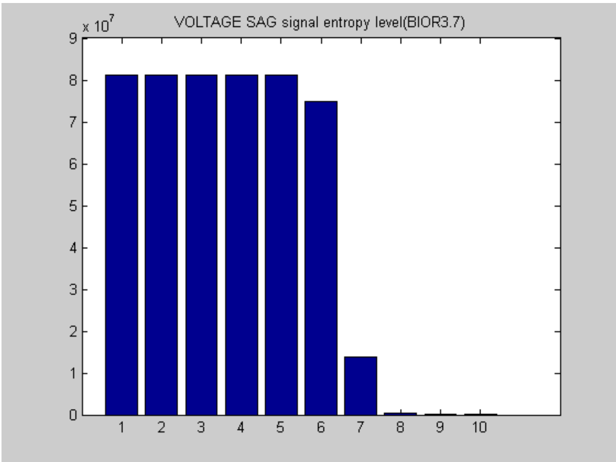
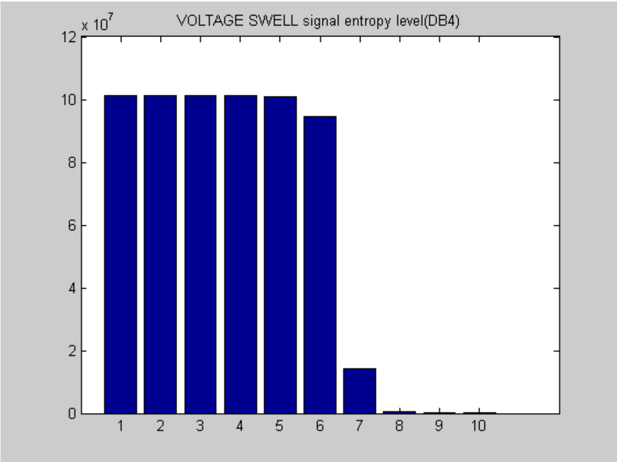
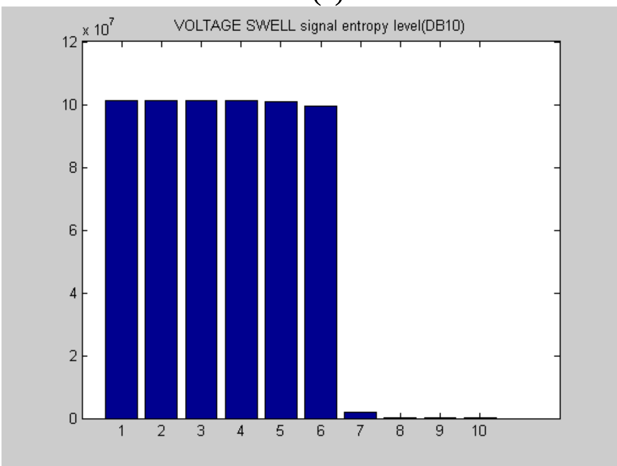


(c)

Fig. 5. Voltage sag signal entropy levels (a) for DB4 wavelet up to level ten decomposition, (b) for DB10 wavelet up to level ten decomposition, (c) for BIOR3.7 wavelet up to level ten decomposition



(a)



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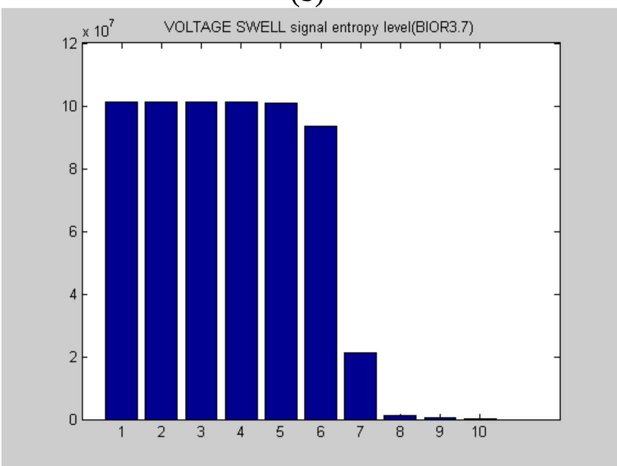

(c)

Fig. 6. Voltage swell signal entropy levels (a) for DB4 wavelet up to level ten decomposition, (b) for DB10 wavelet up to level ten decomposition, (c) for BIOR3.7 wavelet up to level ten decomposition

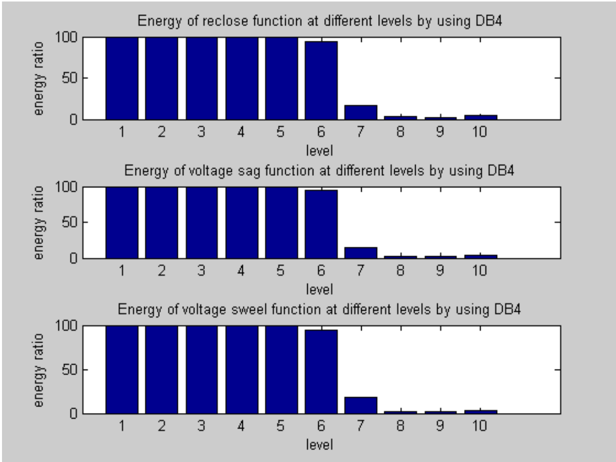

Fig. 7. Energy levels of failure signals by using DB4 wavelet

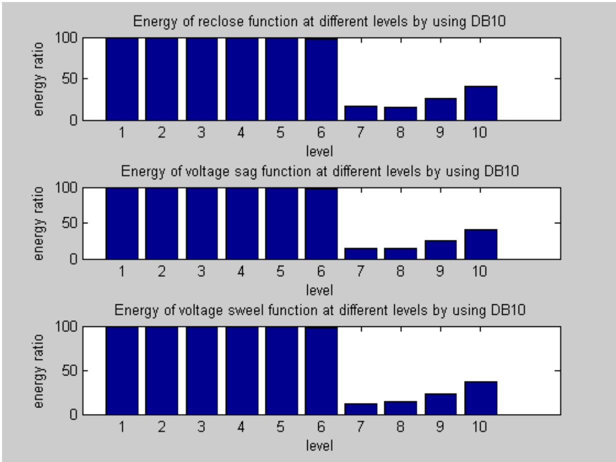

Fig. 8. Energy levels of failure signals by using DB10 wavelet

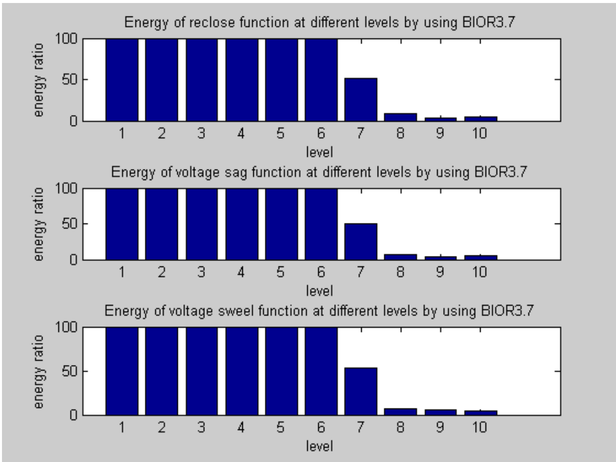

Fig. 9. Energy levels of failure signals by using BIOR3.7 wavelet

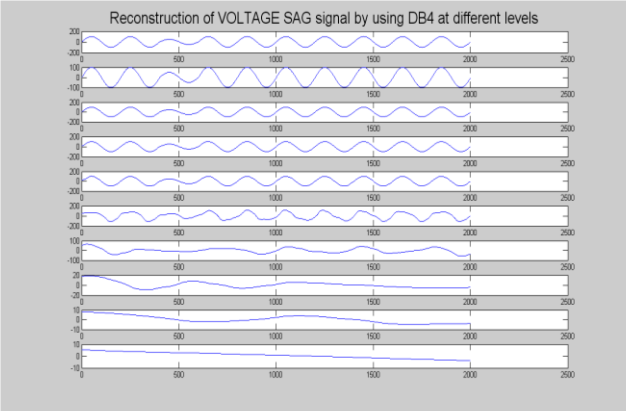

Fig. 10. Reconstruction of the voltage sag signal by using DB4 wavelet at different levels

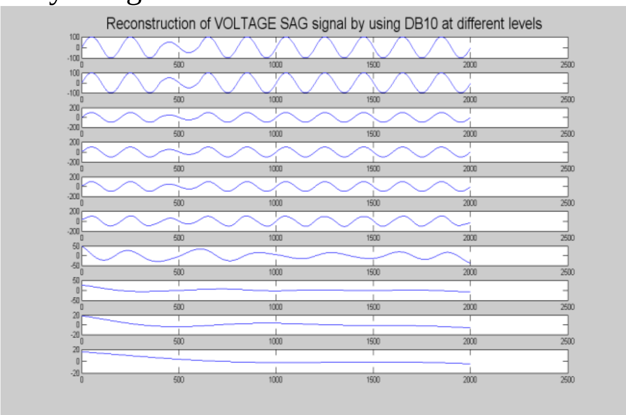

Fig. 11. Reconstruction of the voltage sag signal by using DB10 wavelet at different levels

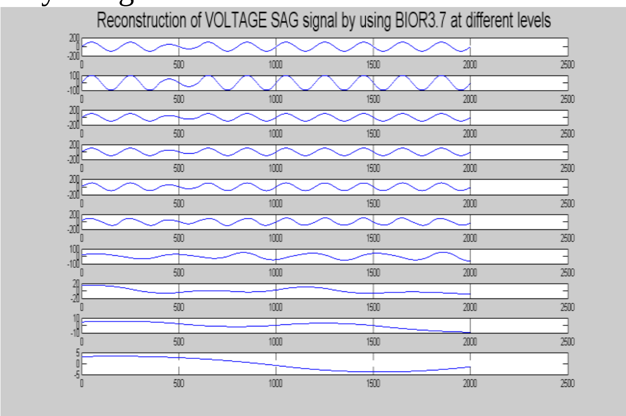

Fig. 12. Reconstruction of the voltage sag signal by using BIOR3.7 wavelet at different levels

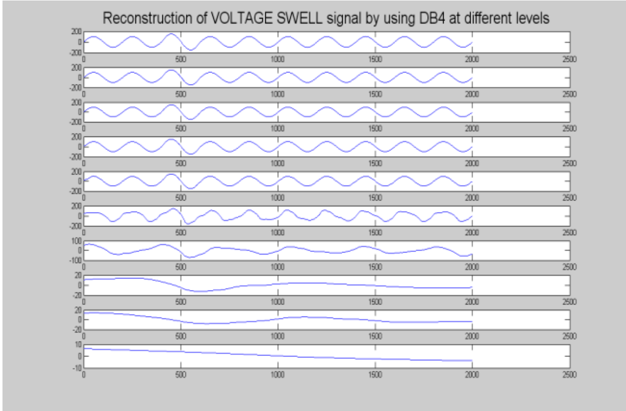

Fig. 13. Reconstruction of the voltage swell signal by using DB4 wavelet at different levels

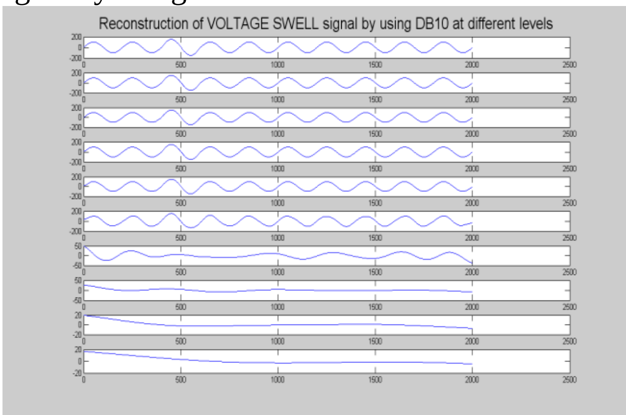

Fig. 14. Reconstruction of the voltage swell signal by using DB10 wavelet at different levels

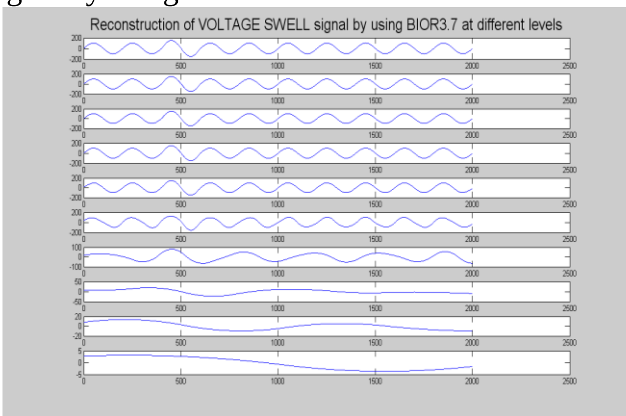

Fig. 15. Reconstruction of the voltage swell signal by using BIOR3.7 wavelet at different levels

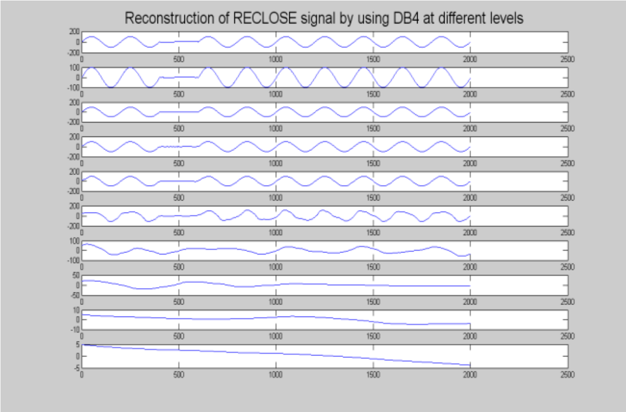

Fig. 16. Reconstruction of the reclose signal by using DB4 wavelet at different levels

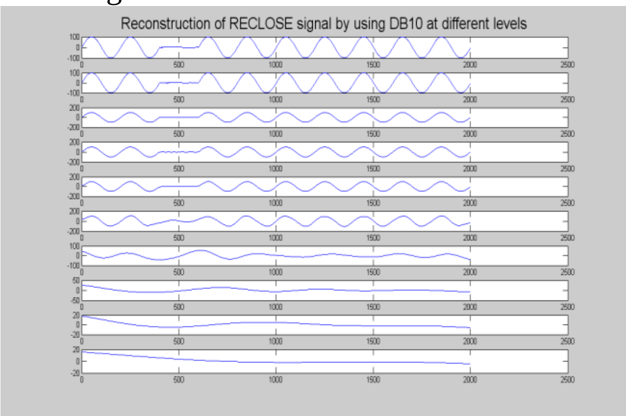

Fig. 17. Reconstruction of the reclose signal by using DB10 wavelet at different levels

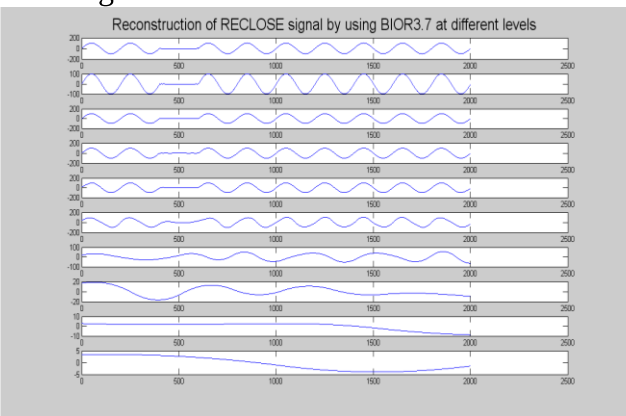

Fig. 18. Reconstruction of the reclose signal by using BIOR3.7 wavelet at different levels