SERBIAN JOURNAL OF ELECTRICAL ENGINEERING
Vol. 3, No. 1, June 2006, 19 - 31

Analysis of High Impedance Transients and Improved Data Compression Using Wavelet Transform

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Abstract: High impedance transients are difficult to detect and classify by using conventional methods due to low transient current [1]. This paper proposes an alternative technique to detect and classify the high impedance transient by obtaining the energy curve from the wavelet co-efficient at each level. The scheme recognizes the distortion of the voltage and current waveforms caused by the arcs usually associated with high impedance fault. From the results obtained it can be inferred, that the energy level of each transient disturbance has unique deviation from pure sinusoidal waveform in particular energy level, which is adopted to provide reliable classification of the type of transient. Also, this paper proposes a novel technique for disturbance data compression which is called as Improved Disturbance Compression Method (IDCM). In this method, only the disturbance data is compressed not the whole waveform using sparse representation property of Wavelet Transform.

Keywords: Wavelet transform, Fault detection, Power quality disturbance, Data compression.

1 Introduction

One of the main problems experienced by manufacturing industries is the distortion in the electrical supply due to high impedance transient apart from normal transient. By definition, high impedance transient does not draw enough current to cause conventional protective device to operate, therefore high impedance fault represent one of the most difficult protection problems in power distributions systems today [2]. These faults often occur when an overhead conductor breaks and falls on high impedance surface such as asphalt road, macadam, sand, cement, grass or tree. When this type of fault happens, energized high-voltage conductors may fall within reach of personnel. In addition, as the arcing often accompanies with these faults, it further poses s fire hazard. Therefore, from both public safety and operational reliability viewpoints, the

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detection of high impedance transients is critically important. To avoid such a situation sources of transient must be known and controlled. This can be first detected and classified.

Recently various method have been proposed to detection schemes based on Fractal techniques [3], Expert systems [4], Neural networks [5] and Wavelet Transform in high frequency noise patterns [6,7]. They offer potential solutions to these problems currently associated with conventional schemes. While direct calculation of fractal dimensions is not effective due to relatively short data sets available for estimation, the use of high frequency harmonics is not feasible in practical relay because of the filtering by substation current transformers. None of them present the real time classification methodologies that can be used to classify the different power quality problems. Discussions of such serious consequences caused by faults are not dealt. Hence, this paper proposes a new technique for detection and classification of fault using Wavelet Transform based on energy curve. This curve, "Magnify" the deviations of the signal with disturbance from the corresponding pure sinusoidal one.

Typically power transient covers a broad frequency spectrum. Each disturbance generates mega bytes of data, in a single capture storing the entire power quality disturbance. The efficiency of Wavelet Transform applied to data compression for Power Quality (PQ) evaluation is demonstrated in [8]. As far as PQ evaluation is concerned, Data Compression methods based on Wavelet Transform shows an improvement in the Compression Ratio (CR) that has never been observed before. However, such methods do not explore the so-called sparse representation property of wavelet transform entirely, since they deal with the transient (non stationary) components along with the sinusoidal (stationary) components. In fact, the property of sparse representation of the Wavelet Transform is due to its suitability for processing the transient or short-time events, such as events produced by load transients, ground faults, dips, lighting strikes, and other kinds of disturbances covering a broad frequency spectrum from kilohertz to megahertz. The present work focuses on the main issues concerning the sparse representation property of the Wavelet Transform to present a new data compression approach IDCM. Two practical problems must be overcome in the above methods.

1) Adopting directly the DWT (Discrete Wavelet Transform) coefficients requires large memory space and enhances the accuracy of recognizing the disturbance type.

2) The decomposition level with the number of extraction features must be reduced to enhance computing efficiency.

This paper is organized in the following manner. Section II deals with Discrete Wavelet Transform. Section III presents proposed methods for fault detection, classification and data compression. Computer simulation results and discussion are provided in section IV. Finally, concluding remarks are given in section V.

2 Discrete Wavelet Transform (DWT)

The Wavelet Transform is one of the mathematical tools for analyzing the non-stationary signal in both time domain as well as frequency domain, which decomposes the given signal into two components vith detailed and approximate components. The complete mathematical relations of detailed and approximate co efficient are given [7]. The Daubechies 4 (D4) wavelet is more localized than the other Wavelet.

Consider λ_j to be an input discrete time signal. The given signal is decomposed into a detailed and approximate representation. By applying wavelet transform, the decomposed signals at stage1 are λ_{j-1} and γ_{j-1}, where λ_{j-1} is approximate co-efficient and γ_{j-1} is the detailed co-efficient of the given input signal λ_j. They are defined in (1) and (2). Further decomposition is defined in (3) and (4) the properties and detailed mathematical relation of Wavelet Transform is given [12].

$$\lambda_{j-1}(k) = \sum_m h(m-2k)\lambda_j(m), \tag{1}$$

$$\gamma_{j-1}(k) = \sum_m g(m-2k)\lambda_j(m), \tag{2}$$

$$\lambda_{j-2}(k) = \sum_m h(m-2k)\lambda_{j-1}(m), \tag{3}$$

$$\gamma_{j-2}(k) = \sum_m g(m-2k)\lambda_{j-1}(m), \tag{4}$$

where $h(m)$ and $g(m)$ are the filter co-efficient that decompose λ_j into λ_{j-1} and $\gamma_{j-1,}$ approximated and detailed respectively.

Then the reconstruction is carried out by reverse processing of signal decomposition. The implementation of reconstruction is straightforward. The mathematical relation for signal reconstruction is given by relation (5), (6) and (7). The condition for perfect reconstruction is as follows:

$$G \cdot G' + H \cdot H' = 1\,, \tag{5}$$

$$g'(n) = (-1)^{n+1} h(n)\,, \tag{6}$$

$$h'(n) = (-1)^{n+1} g(n)\,. \tag{7}$$

3 Disturbance Detection, Classification and Compression

A. Detection Duration of Electromagnetic Transients

In general, when a transient disturbance occurs, the stable power signal will generate a discontinuous state at the start and end points of the disturbance duration. Employing the DWT technique to analyze the distorted signal through one-level decomposition of the MRA will cause the wavelet coefficients at the start and end points of the disturbance to generate severe variation. Therefore, we can easily obtain the start time t_s and end time t_e of the disturbance duration from the variations in absolute wavelet coefficients and calculate the disturbance duration t_t. To filter the noise and correct t_t, the wavelet coefficients need to be modified by subtracting the standard deviation of the absolute wavelet coefficients from the absolute wavelet coefficients.

$$t_t = |t_e - t_s| \tag{8}$$

From the results presented in Figs. 1b, 2b and 3b it can be seen that the Wavelet Transform provides visual detection of the PQ disturbance and duration. However, so far, there is no sufficient evidences of what sort of disturbance occurred at this signal. This will be discussed in the following subsection.

B. Classification

As seen in (9), the energy of the distorted signal can be partitioned at different resolution levels in different ways depending on the PQ problem. Therefore, we will examine the coefficient ω of the detailed version at each resolution level to extract the features of the distorted signal for classifying different PQ problems. The process can be represented mathematically by (10).

$$\sum_{n=1}^{N}|f(n)|^2 = \sum_{n=1}^{N}|\lambda_j(n)|^2 + \sum_{j=1}^{J}\sum_{n=1}^{N}|\gamma_j(n)|^2 , \tag{9}$$

$$P_j = \frac{1}{N_j}\sum_k |\omega_{j,k}|^2 = \frac{\|\omega_j\|^2}{N_j} , \tag{10}$$

$$P_j^D = (P_j)^{\frac{1}{2}} , \tag{11}$$

where $\|\omega_j\|$ is the norm of the expansion coefficient ω_j.

Four special properties in (10) need further explanation.

- The Daubanchie “db4” wavelet function was adopted to perform the DWT, thus resulting in the larger energy

- distributions of the decomposition levels 6, 7 and 8. However, using different wavelet functions will generate different results.
- The energy distribution remains unaffected by the time of disturbance occurrence.
- The outline of energy distribution remains the same despite variations in the vibration amplitude of the same disturbance type.
- The low-level energy distribution will show obvious variations when the distorted signal contains high-frequency elements. On the contrary, the high-level energy distribution will show obvious variations when the distorted signal contains low-frequency elements.

To display clearly the characteristics of the above properties, we normalize (10) by (11).

In this study, we will perform a 12-level decomposition of each discrete distorted signal to obtain the detailed version coefficients. Using (8), we can obtain the disturbance duration by the squared wavelet coefficients of one-level decomposition. Simultaneously, with (10) and (11), we can obtain each detailed energy distribution. The result of the energy distribution diagram is illustrated in Figs. 1c, 2c and 3c. This curve "Magnifies" the deviations of the signal with disturbance from the corresponding pure sinusoidal one.

C. Data compression

In conventional data compression schemes, the input signal frame from the acquisition equipment is applied straightly to a waveform coding technique based on Wavelet Transform. Its performance is limited not only because the transient components of the acquired signal are compressed along with the fundamental or stationary component. Due to the presence of this periodical term, that degrades the waveform coding technique performance.

The discrete signal $x(n)$ acquired from a chosen power line, is modeled by

$$x(n) = S(n) + v(n) \tag{12}$$

$$x(n) = \sum_{i=0}^{I} A_i \cos(n\omega_i + \theta_i) \tag{13}$$

where $x(n)$ is data signal, $S(n)$ represents sinusoids and $v(n)$ is disturbance phenomenon.

With regard to the transient component $v(n)$, a good choice for waveform coding is the application of the wavelet transforms to the transient component of the signal in order to characterize such event with a few significant coefficients. This is, in fact, the major objective of Wavelet Transform for data compression purposes. The discrete version of the wavelet transform is given by (14) and (15) and its fast evaluation is performed using (1) – (4)

$$DWT(m,n) = 2^{-m/2} \sum_{m} \sum_{n} S_T(n) \psi\left(\frac{t - n2^m}{2^m}\right) \tag{14}$$

$$\psi_{m,n}(t) = \frac{1}{\sqrt{a_o^m}} \psi\left(\frac{t - nb_0 a_0^m}{a_0^m}\right) \tag{15}$$

with

$$m, n \in Z,\ a_0 = 2 \text{ and } b_0 = 1.$$

4 Simulation Results

To verify the feasibility of the proposed method, we used the Power System Blockset Toolbox in Matlab to generate one pure sine-wave signal (frequency is equal to 50 Hz, amplitude is equal to 1 p.u.) and three sample transient distorted signals. These distorted signals included the first one is the so-called notching phenomenon which represents a broadband disturbance. The second kind refers to the low-frequency oscillatory transient which represents a narrowband disturbance. The last one is a capacitor switching transient signal. The sampling rate of the digital recorder was 256 points/per cycle. Periods of eight fundamental sinusoid cycles are used in the simulations. The simulink system data are specified as follows:

Source voltage	187.79 kV
Frequency	50 Hz
Series resistance (*Rs*)	0.714 Ω
Series Inductance (*Ls*)	70 mH
Capacitance (C_1)	0.9 μF
Capacitance (C_2)	0.9 μF
Inductance (L_1)	0.13 H
RL Load	R=275 Ω, L=2.25H
Fault Impedance	200 Ω

The parameters to evaluate the waveform coding approach is the Mean Square Error (MSE), the Signal to Noise Ratio (SNR) and Compression Ratio (CR) which are given by (16), (17) and (18). The compression performance is, in turn, assessed by the above parameters.

$$MSE(\mathrm{dB}) = 10\log_{10}\left(\frac{1}{N}\sum_{n=0}^{N-1}\left\|x(n)-\tilde{x}(n)\right\|^2\right), \tag{16}$$

$$SNR(dB) = 10\log_{10}\left(\frac{\sum_{n=0}^{N-1}\left\|x(n)\right\|^2}{\sum_{n=0}^{N-1}\left\|x(n)-\tilde{x}(n)\right\|^2}\right), \tag{17}$$

$$CR = \frac{\mathrm{Original}}{\mathrm{Compressed}}, \tag{18}$$

where $x(n)$, $\tilde{x}(n)$ and $n = 0,1,\ldots,N-1$ are original and reconstructed signal respectively.

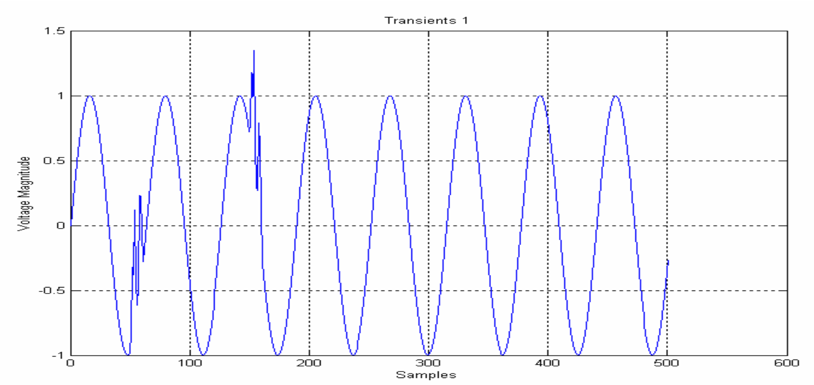
A. Transient 1

Fig. 1 shows the input signal and detailed version of a decomposition and the detailed energy distribution (P_1^D~ P_{12}^D) of a Transient 1 signal. The X-axis is the sampled signal points and the Y-axis is the magnitude in Figs. 1a and 1b. The X-axis is the decomposition level and the Y-axis is the energy in Fig. 1c. The disturbance duration will be set to be very short because the voltage wave shape is disturbed periodically. When transient 1 occurs, (P_6^D, P_7^D, P_8^D) and will show great variations which is marked using circle in Fig. 1c.

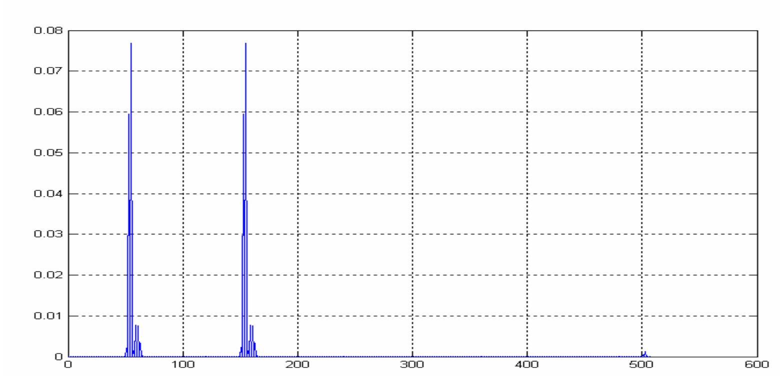
Only the transient event will feed the waveform coding techniques based on DWT. With regard to SNR gain, **Table 1** show comparatively the improvement achieved by the IDCM after lossy compression technique application. Such values are functions of the hard threshold and mother Daubechies wavelet. The proposed method outperforms significantly the performance of the conventional, regarding the SNR and the CR.

Table 1
SNR *and* CR *for Transient* 1.

	IDCM		CONVENTIONAL	
	One level of Decomposition (dB)		Three level of Decomposition (dB)	
Thr (%)	SNR	CR	SNR	CR
5	46.46	13.5	42.81	8.08
10	49.51	19.34	39.21	8.63
15	40.91	20.03	30.33	10.02
20	35.53	21.56	26.97	10.89
25	37.14	22.11	22.65	9.97



(a)



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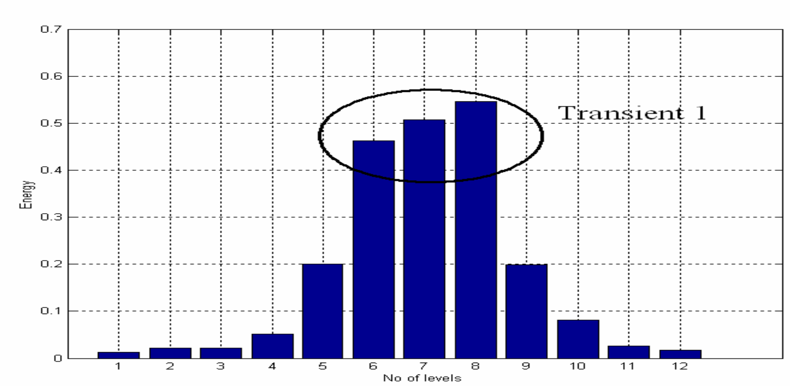
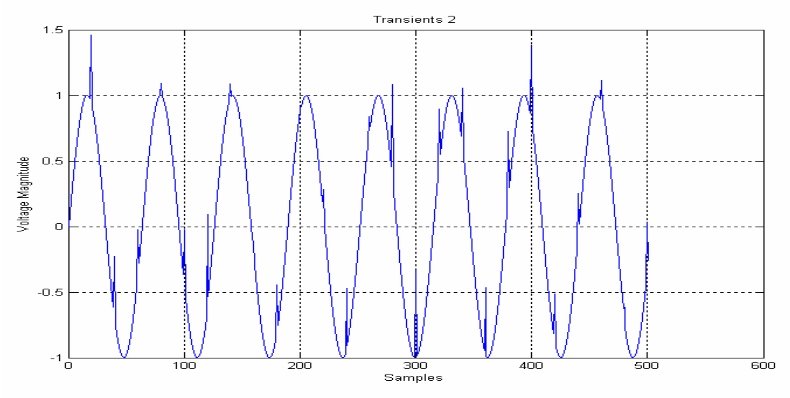


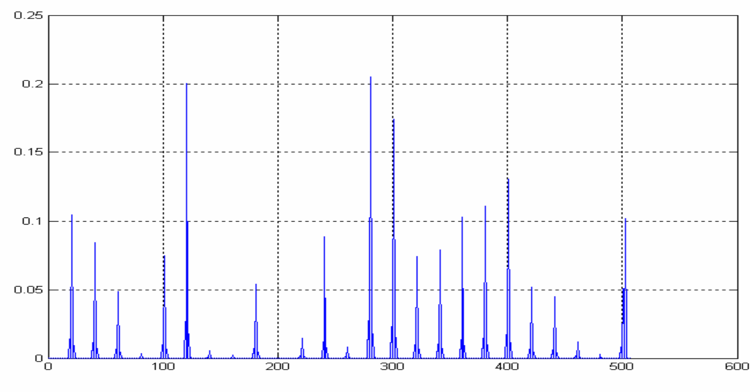
(c)

Fig. 1 – (a) *Transient* 1. (b) *Detailed coefficient*. (c) *Energy Distribution Diagram*.

B. Transient 2



(a)



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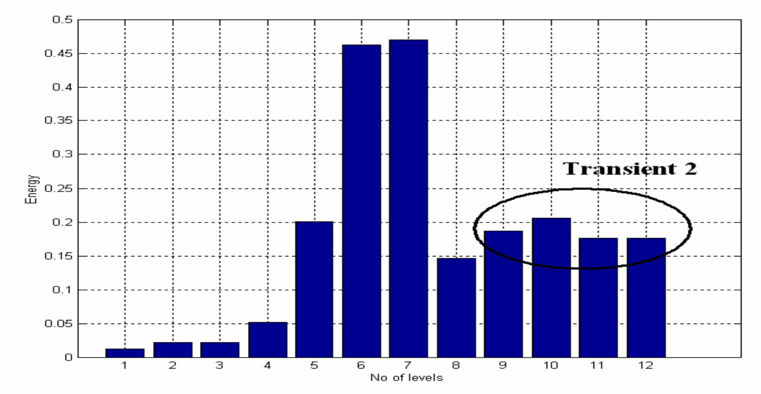

(c)

Fig 2 – (a) *Transient 1*. (b) *Detailed coefficient*. (c) *Energy Distribution Diagram*.

Fig. 2 shows the original and error signals for the simulated narrowband short-time events. When the voltage suffers a transient disturbance of the low-frequency elements such as flicker, P_9^D, P_{10}^D and P_{11}^D will show obvious variations which are highlighted using circle in the Fig. 2c. For this kind of transient, **Table 2** shows the SNR and CR for proposed and conventional method in which proposed method gives better performance for different threshold.

Table 2
SNR *and* CR *for Transient 2*.

	IDCM		CONVENTIONAL	
	One level of Decomposition (dB)		Three level of Decomposition (dB)	
Thr (%)	SNR	CR	SNR	CR
5	35.20	39.06	37.90	23.15
10	32.16	42.13	30.92	25.34
15	30.91	44.12	26.39	26.22
20	27.67	45.18	25.36	27.37
25	24.53	50.07	21.16	28.98

C. Transient 3

The third (capacitor switching) transient signal is depicted in Fig. 14. The error signal contains the non estimated harmonic component and the short-time event. When the voltage suffers a transient disturbance of the high-frequency elements such as capacitor switching and harmonic distortion, P_3^D, P_4^D and P_5^D will show obvious variations which is highlighted using circle in Fig. 3c. CR and SNR obtained in which proposed method gibes better results. **Table 3** confirms such results.

Table 3
SNR *and* CR *for Transient 3*.

	IDCM		CONVENRIONAL	
	One level of decomposition(dB)		Three level of decomposition(dB)	
Thr(%)	SNR	CR	SNR	CR
5	37.09	23.23	40.29	20.60
10	30.16	32.44	30.48	26.62
15	25.69	33.55	26.29	28.52
20	24.67	34.98	25.36	29.42
25	21.97	35.21	21.93	28.08

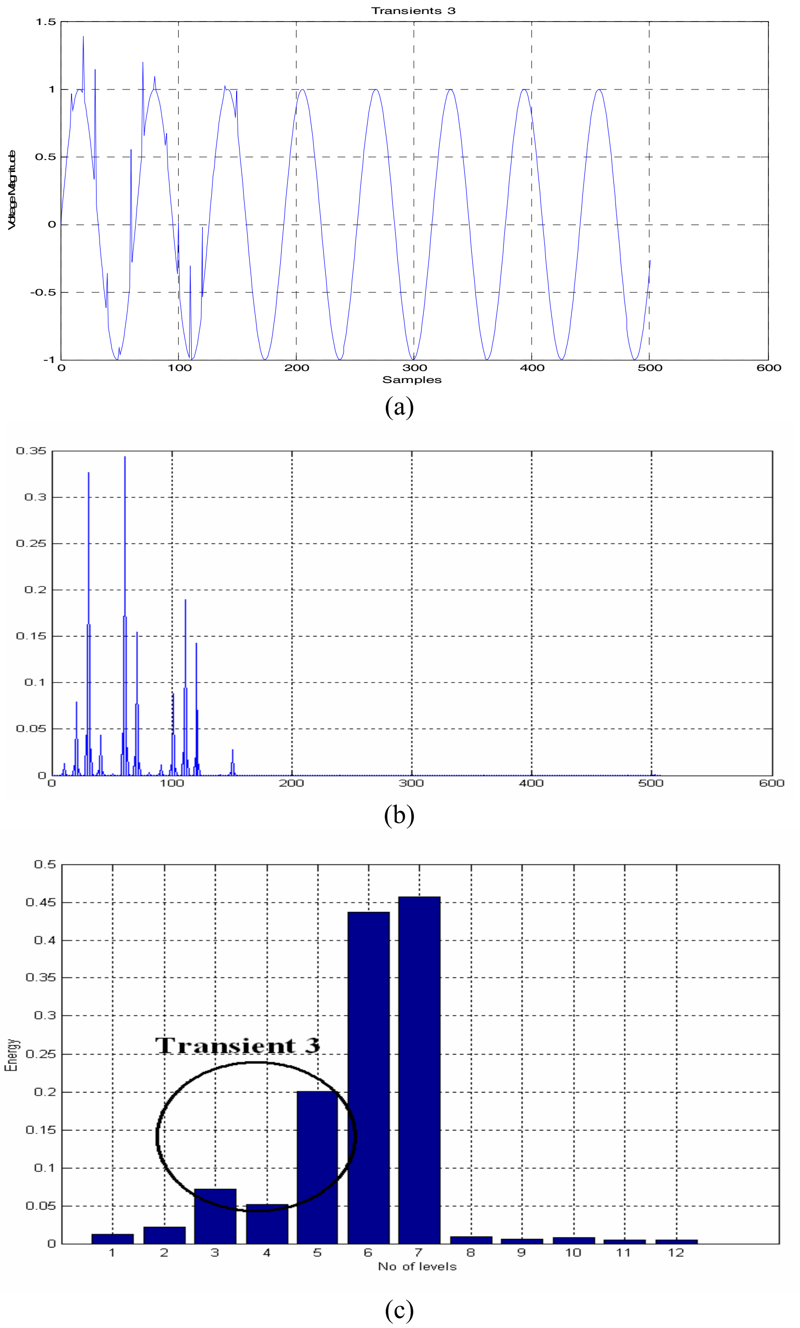

Fig. 3 – (a) *Transient 1*. (b) *Detailed coefficient*. (c) *Energy Distribution Diagram*.

5 Conclusion

This paper proposes a modified approach for the high impedance fault detection, classification and compression of large quantity data obtained for analysis of high impedance transient in power system. The results presented in this paper obtained by applying the modified algorithm shows better performance compared with conventional methods in terms better classification and SNR and MSE. The Wavelet Transform contour displays significantly improved patterns to detect, localize and visually classify the types of violations.

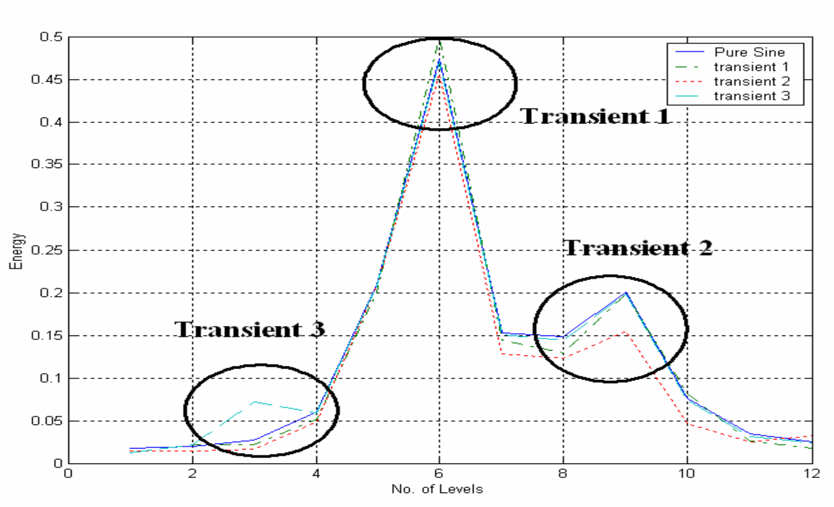

Fig. 4 – *Differences in energy distribution of all signals.*

Fig. 4 shows orderly the energy distributions of four signals on the same coordinate axis. Thus, we can clearly observe the differences in energy distribution between different signals. Further, the results presented that the signal can be perfectly reconstructed from the compressed signal in order to save space using Wavelet Transform. Thereby data storage requirement and transmission time will be minimized while preserving the reconstruction signal in such a way that it is virtually indistinguishable from the original. Also by using features in the waveform signatures, automated recognition can be carried out.

6 References

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