EFFECTIVENESS OF WAVELET FAMILIES FOR POWER QUALITY EVENT QUANTIZATION

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ABSTRACT

Wavelet Packet Transform technique is used to estimate the Power Quality Disturbances. This paper exploits the usage of diversified kinds of wavelet families for Wavelet Transform, which can be potentially employed in quantizing the Power Quality Disturbances with accurate precision. The detection process is carried from the energy content of the transformed signals. Different wavelets viz Symlets, coiflet wavelets, biorthogonal wavelets and Daubechius wavelets are developed for detection. These wavelets are simulated and studied under the MATLAB environment. The result clearly shows the intrinsic worth of Daubechius and biorthogonal wavelets over the other wavelets taken into concern.

Keywords: power quality events, wavelet packet transform (WPT), time-frequency analysis, wavelet families- daubechius, symlet, coiflet and biorthogonal wavelet.

1. INTRODUCTION

The major concern for both the electric supplier and the electric consumer is the quality of the power that is delivered. The variation of power frequency and other fundamental determinants of electric power possess a serious threat to utilities, generating and distributing power, which may lead to the reduced life span of the devices, disoperation, instability, interruption, reduced efficiency, etc in the utility side. In order to minimize the effect of disturbances in grid connected network, it is vital to take actions in the network that leads in nullifying the causes and effects produced by the Power Quality Disturbances (PQD). From the extensive research works that are available, the major causes for the poor Power Quality (PQ) is the occurrence of voltage sags which accounts for most of the PQDs [1]. In addition to sags various disturbances like swell, harmonics, interruption, notch and flicker also accounts for poor PQ.. Owing to the increase in the demand of clean power supply by the consumers, the power utilities are in look for automated and precise PQ monitoring systems. For improving the PQ the utilities must collect the real time information about the line parameters, mainly voltage information's through their Data-Acquisition systems (DAC). Once the information is obtained, appropriate data mining techniques has to be employed to analyze the causes and the sources for the disturbances. It is very essential for the system to identify the type of disturbances precisely and more quickly, since the disturbances may be intermittent [2]. Early days, in the later 1980s point to point comparison of the obtained raw data is considered with the sequential cycles for the detection of PQ problems [3]. Later on there were wide developments in signal and image processing techniques which are being implemented in power systems, extensively in analysing PQ events, detection, measurement and localization.

The Fourier Transform (FT) is not a suitable tool for analysis of PQ disturbances since it does not provide any information about time localisation which is more essential to find start time, end time of the disturbance and also the interval of the disturbance. The FT provides the accurate spectral information of the power signal [4]. The modified form of FT is the Short Time Fourier Transform (STFT). STFT is well suited for stationary signals wherein there is no much frequency variation with respect to the time. The STFT has a fixed window width; hence it does not recognise the signal dynamics of the non-stationary signals [5]. Hence WT can be used as an alternative to STFT to look at the power signal at various scales and locations. WT provide accurate frequency and time localization. The properties of WT and their usage in scenario similar to that of power signals [6] justify the usage for analyzing the power signals. The underlying fact of wavelet that it integrates to zero shows the ability of the standard deviation of different resolution levels to localize the spectral content of the power signal. The CWT will decompose the power signal frequency into multiple wavelets. By varying the transition and dilation parameters, each decomposed wavelets can be obtained with different location and dilations. The CWT follows a time-scale analysis and not a time-frequency analysis pattern hence there must be a proper transformation between the scale and frequency [7]. The CWT is also combined with FT for quantifying the power signals [8]. In that case the steady state stationary signals can be characterized by the FT and the transient signals are characterized by the CWT. Another method of WT combined with short-time correlation transform (STCT) is introduced for detecting the signal deviations with enhanced performance [9].Even though CWT provides redundant information regarding the spectral of power frequency signals, DWT is widely used. DWT is derived from CWT, but the relationship is different from the properties concerned with Fourier Transform and Discrete Fourier Transform. The DWT is based on a multiresolution analysis (MRA) wherein the original signal is decomposed into two approximated signal and detailed signal based on the scaling and wavelet functions respectively [10].

The detection of PQ event through WPT depends on the type of mother wavelet being chosen. Once the mother wavelets are chosen the obtained digital signals are decomposed into five levels and reconstructed according to the nature of the wavelet under consideration. The decomposition and reconstruction yields the approximate and detailed signals respectively. By the comparison of spectral contents in the pure sinusoidal signal of power frequency and the PQDs, a comparison is drawn between the two, which yields accurate quantization. For this purposes five wavelets viz symlets, coiflets, biorthogonal, haar and daubechius wavelet are considered in MATLAB environment. Their performance under various PQ variations are studied and tabulated in this paper.

2. DETECTION METHODOLOGY

Wavelet Transform technique is employed here to detect the PQD. A wave like function, called as wavelet, transforms the signal under study into another signal representation that provides more useful information about the original signal. This transformation is called as the Wavelet Transform. This transformation produces a scalable window that gives proper resolution of the time and frequency [11].

A. Continuous wavelet transform

The Continuous Wavelet transform (CWT) of a signal x(t) is stated as

$$\mathrm{CWT}(a,b) = \int_{-\infty}^{+\infty} x(t) * \frac{1}{\sqrt{a}} * \Psi\left(\frac{t-b}{a}\right) dt \qquad (1)$$

The expression is a scaled and shifted version of the mother wavelet Ψ (t). The parameter 'a 'corresponds to scale and frequency domain property of Ψ (t).The parameter 'b' corresponds to time domain property of Ψ (t). In addition is the normalization value of signal for having spectrum power as same as mother wavelet in every scale.

B. Discrete wavelet transform

In the Discrete Wavelet Transform, to avoid redundancy the base functions are discretely generated. It is obtained by choosing the parameters a and b at a certain steps that can be expressed as follows: a= a_0^m and b=$nb_0a_0^m$ [12]. Thus DWT can be expresses as

$$DWT(m,n) = 2^{\frac{-m}{2}} \sum_m \sum_n x(n)\, \Psi^*\left(\frac{t-n2^m}{2^m}\right) \qquad (2)$$

And the discrete mother wavelet is hence described by

$$\Psi_{m,n}(t) = \frac{1}{\sqrt{a_0{}^m}}\, \Psi\left(\frac{t-nb_0a_0{}^m}{a_0{}^m}\right) \qquad (3)$$

The values of a_0 and b_0 are fixed constants and must be greater than unity and m,n are a set of integers.

C. Multiresolution analysis (MRA)

The WT decomposes the signals into various frequency bands. This is achieved by passing the signal into various high pass filters and low pass filters. Thus the signal can be decomposed into two levels at each frequency bands, approximate signal and detailed signal. The approximate signals are achieved through the High Pass Filters and the detailed signals can be derived from the Low Pass Filters. The approximate signal provides the information about high-scale low frequency components of the embedded signal and the detailed signals provide adequate information regarding the low-scale high frequency components of the original signal. This decomposition process is iterative and the signal can be broken down to many lower and higher resolution components that is termed as the Multiresolution Analysis [13].

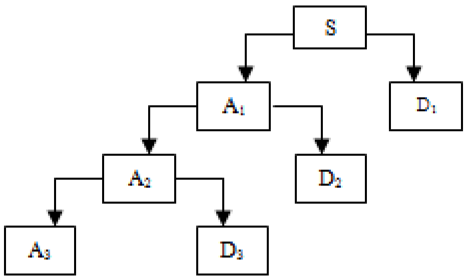

Figure-1. MRA of a signal.

The filtering process at the basic level is shown in the Figure-1, where S denotes any signal that is approximated and decomposed to three levels denoted by A_i and D_i respectively. It denotes only the basic level of filtering, since the resolution is an iterative process, it can be continued indefinitely. Here, in this paper, the decomposition process is carried for 5 levels.

3. WAVELET FAMILIES

There are various wavelet families found in various literatures and the properties of every wavelet is greatly influenced by various factors, the most prominent one is the mother wavelet function (Ψ(t)) and its complex conjugate ($\Psi^*(t)$). The time and frequency localisation of the signal are obtained from these wavelet functions. The rate at which the function converges to zero when the time or frequency tends to move towards infinity signifies the localisation of the information. The wavelet families that are included in the toolbox are listed below in Table-1.

Table-1. List of Wavelet families used for PQD estimation.

Wavelet family	Short name
Haar wavelet	haar
Daubecius wavelet	db
Symlet wavelet	sym
Coiflet wavelet	coif
Biorthogonal wavelet	bior

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Daubechius wavelets: A family of wavelets denoted by dbN, where N represents the order of the wavelet, the simplest of the wavelet, precisely the first order wavelet db1 is the simplest imaginable wavelet, it is called as the haar wavelet, Other than db1, no other daubechius wavelet has a fair mathematical expression. The square modulus of transfer function of haar wavelet exists in simplest form more explicitly.

Let $P(y) = \sum_{k=0}^{N-1} C_k^{N-1+k} y^k$ (4)

Where represents the binomial coefficients, then

$$|m_0(w)|^2 = \left(cos^2\left(\frac{\omega}{2}\right)\right)^N P\left(sin^2\left(\frac{\omega}{2}\right)\right) \quad (5)$$

The transfer function is expressed as follows

$$m_0(w) = \frac{1}{\sqrt{2}} \sum_{k=0}^{2N-1} h_k e^{-ik\omega} \quad (6)$$

The number of times the wavelet tends to zero moment is the order of the wavelet and the support length for the wavelet as well the function ranges upto 2N-1.Almost all dbN are asymmetrical.

Symlet wavelets: Symlets denoted by symN are modified form of the daubechius wavelets, where N represents the order of the daubechius wavelets. The simplicity of the dbN wavelets are retained and the symmetrical property is improved by the modification.

The function obtained in dbN, m_o is reused in symN. The following assumption can be considered, as a function of W, which is. The properties of symlets are same as the daubechius except the fact that symlets are more symmetrical wavelets.

Coiflet wavelets: Named after Coifman who introduced these series of wavelets represented by coifN, where N represented the order of the wavelet. The mother wavelet has 2N zero moments and the function has 2N-1 zero moments. The approximation of a large signal‘s’ for a larger coefficient ‘j’ by a coiflet is described by. The approximation can be considered as an equality when we consider the signal as a polynomial of function ‘d’ such that d is always less than or equal to N-1.

Biorthogonal wavelets: Instead of using single wavelet two wavelets are being used by the biorthogonal wavelets which belong to a special family of the wavelets. These filters are well adapted for subband filtering where the symmetry and exact reconstruction are not possible when the same filters are used for reconstruction as well as decomposition. Thus they require two filter lengths which can be given by bior Nr.Dr. The Nr and Dr are the length of the filters associated with the decomposition and reconstruction respectively. The wavelet used for approximation is and the one used for reconstruction is. If the signal is denoted by‘s’ then the two coefficients are expressed as follows

$$\widehat{c_{j,k}} = \int s(x)\widehat{\Psi}_{j,k}(x)dx \quad (7)$$

$$s = \sum_{j,k} \widehat{c_{j,k}}\ \Psi_{j,k} \quad (8)$$

The two wavelets are also dual in nature under the following condition:

$$\int \Psi_{j,k}(x)\, \Psi_{j'k'}(x)\, dx = 0 \quad (9)$$

When j=j’ and k=k’

Since the two filters are symmetrical in nature, the functions can be easily built numerically than the other wavelets.

4. SIMULATION RESULTS

The wavelet analysis is performed on the simulation tool ‘MATLAB’ run on a 1.7 GHz Intel i3 based processor. The PQD signals are sampled at a frequency rate of 1.28 kHz. The signals are investigated for five level of decomposition using wavelets of various families. The wavelets considered for the analysis are symlet, daubechius wavelet, coiflets and biorthogonal wavelet. The signals are then probed for the type of PQD from the wavelet coefficients acquired during the decomposition. The decomposition is facilitated by the wavelet toolbox programmed in the simulation tool.

The PQ events that are explored in this paper embrace the voltage sag, voltage swell, interruption, harmonics, flicker and notch. The signals are generated under the assumption of voltages having a magnitude of 230 V at 50 Hz by modelling them mathematically [14]. The disturbances are generated for a period of 10 cycles starting at 0.1 s. The signals are tested under noiseless environment.

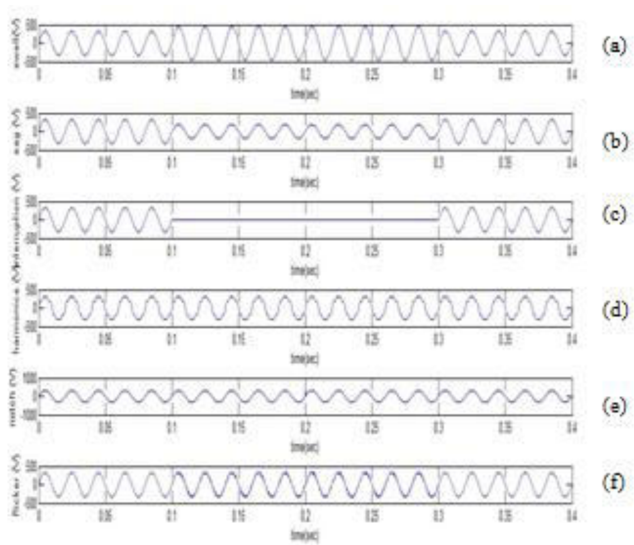

Figure-2. Waveforms considered for decomposition, 2(a) Voltage Swell, 2(b) Voltage Sag, 2(c) Interruption, 2(d) Voltage harmonics, 2(e) Notch and 2(f) Flicker.

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For analysing the PQDs various wavelets are being considered here for the disturbances generated, the haar wavelet is considered first (db1) and the daubechius wavelets are being considered and simulated upto 23 orders (N=2 to N=23). The symlets are also simulated for 20 orders. Coiflets are taken into consideration for 8 orders. Biorthogonal wavelets of order bior2.4 and bior 5.2 are also considered for PQ events detections. For each of the orders taken into consideration, the disturbances are decomposed and reconstructed. The approximation and detailed coefficients are considered for each disturbance until level 5. Figures 4-9 represents the approximate and detail coefficient plots of all the PQDs considered for estimation and Figure-3 shows the plots for a pure sinusoid.

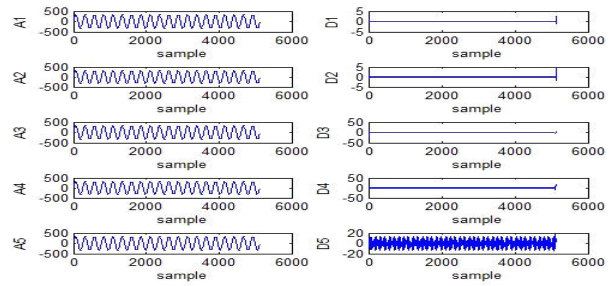

Figure-3. Approximate and detailed coefficients of a pure sinusoid obtained by bior mother wavelet.

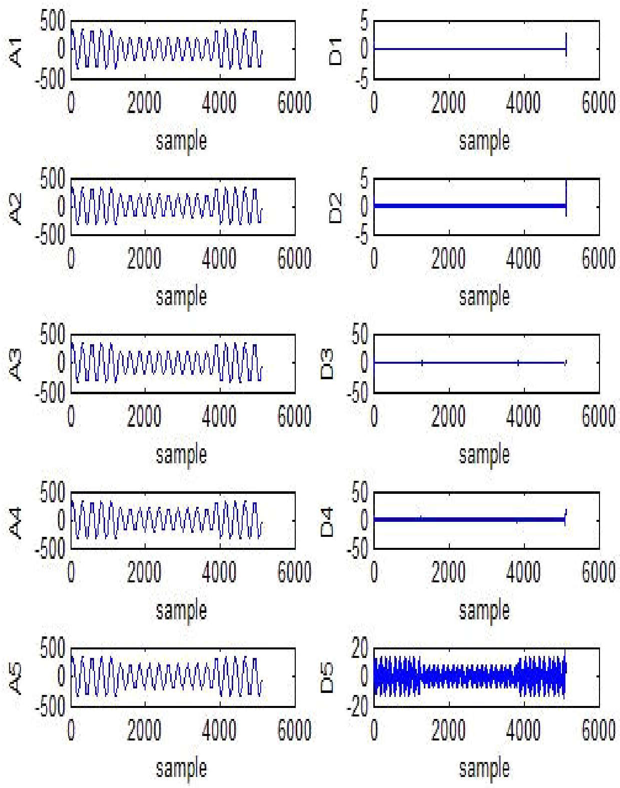

Figure-4. Approximate and detailed coefficients of voltage sag obtained by bior mother wavelet.

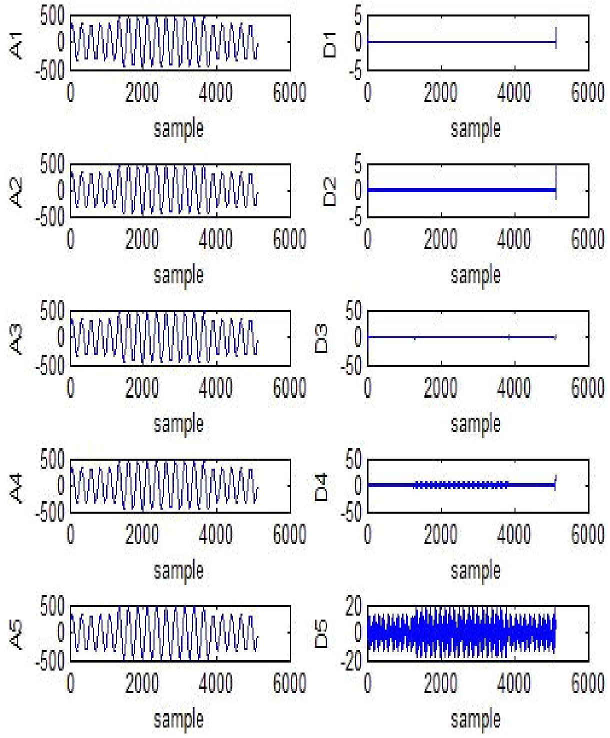

Figure-5. Approximate and detailed coefficients of voltage swell obtained by bior mother wavelet.

An interesting feature of WT can be seen from the third level Detailed coefficients (D3) obtained in Figure-4 , Figure-5 and Figure-6 It clearly denotes the denotes the start time and the end time the disturbances, Here it can be clearly seen that the disturbance starts at the 1720th sample and ends at 3880th sample. Hence the time localization of the disturbances can be obtained through the WT.

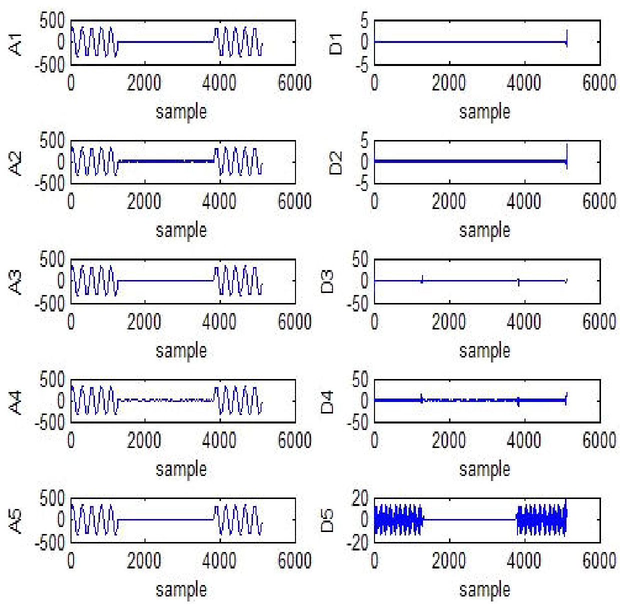

Figure-6. Approximate and detailed coefficients of voltage interruption obtained by bior mother wavelet.

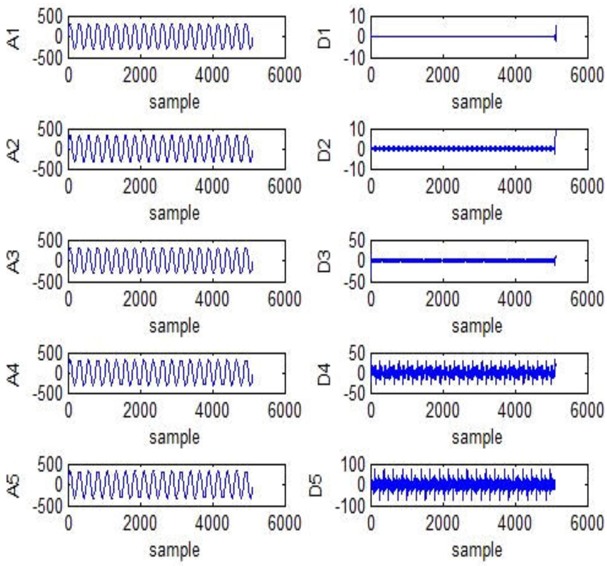

Figure-7. Approximate and detailed coefficients of voltage harmonics obtained by bior mother wavelet.

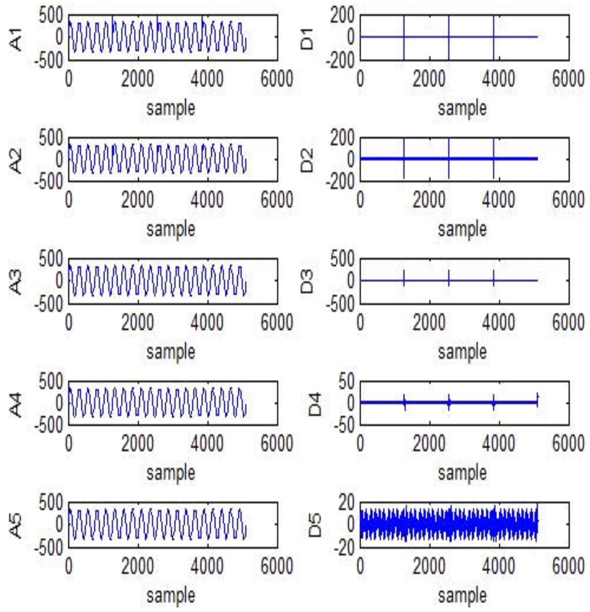

Figure-8. Approximate and detailed coefficients of notch obtained by bior mother wavelet.

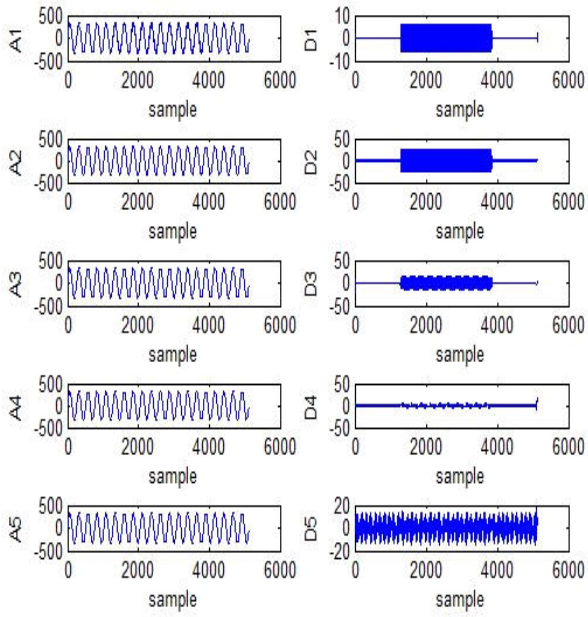

Figure-9. Approximate and detailed coefficients of flicker obtained by bior mother wavelet.

The RMS values of the approximate and the detailed coefficients obtained in the decomposition and reconstruction of signals are compared with the obtained results of a pure sinusoid. Specific order of wavelet coefficients are found to deviate significantly from the pure sinusoid, which can be taken for classification. Biorthogonal wavelets, in specific bior2.4 and daubechius wavelets are found to me more appropriate in classifying the PQDs. The daubechius wavelet of lower order (db4) is most suited for disturbances that have gradual changes like voltage sag, swell, interruption and harmonics, whereas sudden time varying disturbances like notch, flicker are extracted with less precision by higher order daubechius wavelets (db8).

The RMS values of the approximate and detailed signals in pu obtained by the biorthogonal wavelet are tabulated in Table-2.

Table-2. Approximate and detailed signals of PQDs.

PQD	A5	D5	D4	D3	D2	D1
Swell	3362.3	99.44	99.242	22.254	00.88	00.298
Sag	3308.3	99.66	99.78	22.59	00.84	00.36
Interruption	3305.5	111.81	110.16	33.18	00.87	00.37
Harmonics	345.4	221.46	220.57	11.28	00.13	00.004
Notch	4406.9	33.34	550.68	117.59	11.39	00.16
Flicker	3355.7	115.17	11.32	00.91	00.19	00.003
Pure Sine	3337.7	66.639	11.53	00.09	00.92	00.389

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The Table clearly shows that decomposition coefficient A5 for sag and interruption is significantly lesser than the pure sinusoid. For harmonics and flicker the approximate coefficient A5 and detailed coefficient D5 are quite higher than a pure sinusoid. All the coefficients mentioned above except D5 are greater than pure sinusoids for notch. These deviations can be used for estimating the type of disturbances more precisely and accurately. Also for harmonics and flicker D1 and D2 are slightly lesser than the pure sinusoid. With these significant changes of the disturbance from the pure sinusoid, the PQDs can be easily quantized.

CONCLUSIONS

This work provides a study on various mother wavelets that can be used to perform the Wavelet Transform technique on electric power signals for extracting vital information about the deviations from the ideal signals. Using the energy content as a performance index of the signal the detection process is carried out. The results clearly show the merits of biorthogonal wavelets and daubechius wavelets over the other wavelets taken into consideration. The symlet mother wavelets extract symmetrical disturbances very well since they resemble the daubechius wavelets, but as the order of symlets increases they are not able to localise the spectral content owing to their increased symmetric properties of windows. The approximation in coiflets tends to be equal when the function is a polynomial which is lesser than the filter lengths, hence coiflets of higher orders can only be used. As order increases there is increased symmetric property of window like a symlet. The lower order daubechius wavelets can be used to detect stationary and periodic disturbances whereas the higher order daubechius wavelets detects time varying sudden disturbances. This also gives an indication of how the width of the window influences the detection methodology. The biorthogonal wavelets offer much precision in detecting the disturbances but the presence of two filters, one for decomposition and one for reconstruction makes the process more cumbersome as it involves lot of computation time. From the simulation of the same signals, the time taken for computing bior wavelets is 6.060398 seconds and for a daubechies is 5.399150 seconds

REFERENCES

[1] Bollen MHJ, Understanding Power Quality Problems: Voltage Sags and Interruption, IEEE Press, New York, 2000, pp. 193-196.

[2] IEEE Std. 1159-2009, IEEE Recommended Practice for Monitoring Electric Power Quality, IEEE Inc., New York, USA, 2009.

[3] R.A. Flores, State of the Art in the Classification of Power Quality Events, an Overview, in: 10th IEEE ICHQP, vol. 1, 2002, pp. 17-20.

[4] A.C. Parsons, W.M. Grady, E.J. Powers, A Wavelet-Based Procedure for Automatically Determining the Beginning and End of Transmission System Voltage Sags, IEEE PES Winter Meet. 2 (1999) pp. 1310–1315.

[5] M. Kezunovic Automated Analysis of Voltage Sags, their Causes and Impacts, IEEE PES Summer Meet. 2 (2001) pp. 1113–1117.

[6] P.F. Ribeiro, Wavelet Transform: An Advanced New Tool for Analyzing Nonstationary Harmonic Distortion in Power Systems, IEEE International Conference on Harmonics and Power Systems (1994) 365–369.

[7] H. Mota, F.H. Vasconcelos, R.M. da Silva, Real-Time Wavelet Transform Algorithms for the Processing Of Continuous Streams of Data, in: IEEE International Workshop on Intelligent Signal Processing, 2005, pp. 346–351.

[8] J.C. Montano, M. Castilla, A. Lopez, J. Gutierrez, C. Bravo, D. Borras, Analysis of Electrical Signal Disturbances, a New Strategy, International Conference on Renewable Energies and Power Quality. (2004) pp. 1–6.

[9] T.K. Abdel-Galil, E.F. El-Saadany, M.M.A. Salama, Power Quality in Deregulated Power Systems, IEEE PES Winter Meet. (2002) pp. 952–958.

[10] M.A.S. Masoum, S. Jamali, N. Ghaffarzadeh, Detection and Classification of Power Quality Disturbances Using Discrete Wavelet Transform and Wavelet Networks, IET Journal on Science, Measurement and Technology, 4 (2010) pp. 193–205.

[11] J. Barros, M. de Apraiz, R.I. Diego, A Virtual Measurement Instrument for Electrical Power Quality Analysis using Wavelets, IEEE Transactions on Measurements. 42 (2009) pp. 298–307.

[12] C.-C. Liao, H.-T. Yang, H.-H. Chang, Denoising Techniques with a Spatial Noise Suppression Method.

[13] Wavelet-Based Power Quality Monitoring, IEEE Transactions on Instrumentation and Measurements. 60 (2011) pp. 1986–1996.

[14] H. Eristi, Y. Demir, an Efficient Feature Extraction Method for Classification of Power Quality Disturbances, International Conference on Power Systems Transients. (2009) pp. 1–6.

[15] Patrick Marchand, O. Thomas Holland, Graphics and GUIs with MATLAB. (CHAPMAD and HALL/CRC, LTD, 2003).