Analysis on Classification of Power Quality Disturbances Using Wavelet Transform

Yasmin Bte Ahmad Kushairi
Faculty of Electrical Engineering
Universiti Teknologi MARA Malaysia
40450 Shah Alam, Selangor, Malaysia
e-mail: yasminkushairi@gmail.com

Abstract— **This paper presents Discrete Wavelet Transform (DWT) as one of the method to classify power quality disturbances. This technique is using Symlets and Daubechies Wavelet family to extract the signal of the disturbance for classification process. The data which contain power quality disturbances such as sag, transient, and notch had been analyzed to show the effectiveness of the proposed technique. The result obtained shoes that wavelet transform manage to analyze and classify the power quality disturbances. (Abstract)**

Keywords- *power quality, discrete wavelet transform, Daubechies, Symlets (key words)*

I. INTRODUCTION

Power quality disturbance may cause a lot of problems to the affected load. It is well known that the main power quality deviations are caused by short circuits, harmonic distortions, notching, voltage sags and swells, as well as transients due to load switching. In order to correct such problems, it its required that they should be detected and identified. Nevertheless, whenever the disturbances last for only a few day cycles, a simple observation of the waveform in a bus bar may not be enough to allow one to recognize that there is a problem in there or, more difficult yet, to identify the sort of the problem. On the other hand, the wavelet transform has been adopted if different fields, such as telecommunications and acoustics. In the last decade the wavelet transform has been studied to analyse voltages and currents during short duration disturbances. The main purpose of this paper is to show an approach in which the MATLAB wavelet transforms toolbox is adopted not only to detect power quality problems but also to classify them.

Wavelets have paved a unified framework for signal processing and its application since its emergence [1]. The mathematical functions of wavelets cut up data into different frequency components, hence study each component with a resolution matched to its scale. It is also an improvement of a traditional Fourier transform which rely on a uniform window for spreader frequencies. It also improves the Fourier transform in analyzing physical situations according to scale. Wavelet transforms can apply various lengths of windows according to the amount of signal frequencies. Characteristics of non-stationary disturbance of signals can be investigated by wavelet transforms.

The procedure of wavelet transforms is to adopt a wavelet prototype function, called an *analyzing wavelet* or *mother wavelet*. Original signal or function can be represented in terms of a wavelet expansion while data operations can be performed using just the corresponding wavelet coefficients. Instead of transforming a pure 'time domain' into a pure 'frequency domain', the wavelet transforms find a good compromise in time-frequency domain [2].

II. WAVELET TRANSFORM

A. *Introduction to Wavelet Transform*

Recently, wavelet transform developed signal processing tool enabling the analysis on several timescales of the local properties of complex signals that can present non-stationary zones. Wavelet is the foundation for new technique of signal analysis and synthesis and finds applications to general problems such as compression and denoising [3]. The analysis allows the use of long term intervals where precise low-frequency information can be obtained and from shorter regions, high-frequency information will be obtained [4]. Compared with Fourier transform, wavelet can obtain both time and frequency information of signal, while only frequency information can be obtained by Fourier transform. Figure 1 below shows the wavelet transform:

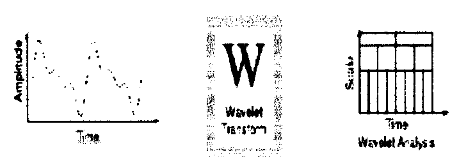

Figure 1: Wavelet Transform

In analyzing signals using wavelet analysis, the signal will go through decomposition process into their approximation and detail signals. Approximation of signal at a given level can be reconstructed by using upsampling and reconstruction filter which will form the approximation and detail coefficients of the level below. The signal is denoted as S, and it can be reconstructed from its first-level approximation and detail coefficients [4].

$$S = A_1 + D_1$$

Where,

S = original signal
A_1 = approximation coefficient at level 1
D_1 = detail coefficient at level 1

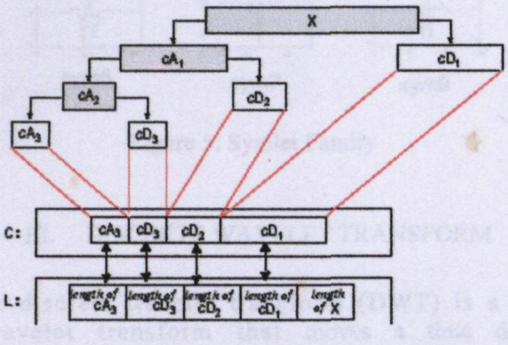

Figure 2: Decomposition Structure of Wavelet Transform

B. Daubechies [3]

Generally for given support width $N=2A$, the Daubechies wavelets are chosen to have the highest number A of vanishing moments, but it does not imply the best smoothness. It is among the 2^{A-1} possible solutions the one is chosen whose scaling filter has external phase. Daubechies wavelets are widely used in solving a broad range of problems such as self-similarity properties of a signal or fractal problems, and signal discontinuities.

Daubechies is the first one to possibly handle orthogonal wavelets with compact support and arbitrary regularity. This family contains the simplest and oldest of wavelets, which is Haar wavelet, db1. The wavelet is discontinuous, resembling a square form as shown below.

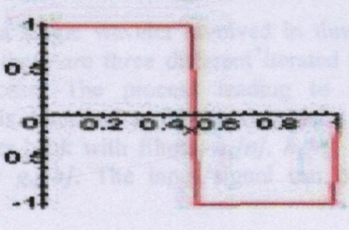

Figure 3: Haar Wavelet

The Haar wavelet is defined by:

$$\psi(x) = 1 \; if \; x \in [0,0.5], \psi(x) = -1 \; if \; x \in [0.5,1] \; and \; 0 \; if \; not.$$

The associated scaling function is the function:

$$\psi(x) = 1 \; if \; x \in [0,1] \; and \; 0 \; if \; not.$$

The wavelets of this family do not have explicit expression except for db1. However, the square modulus of the transfer function of the associated filter h is explicit and relatively simple.

Let $\sum_{k=0}^{N-1} C_{N-1+k}^{k}\, y^k$, where C_{N-1+k}^{k} are the binomial coefficients. Hence:

$$|m_0(\omega)|^2 = \left(\cos^2\left(\tfrac{\omega}{2}\right)\right)^N P\left(\sin^2\left(\tfrac{\omega}{2}\right)\right)$$

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

Properties of this family are:

- The ψ and φ support length is 2N-1. The number of zero moments of ψ is N.
- dbN wavelets are asymmetric (in particular for low values of N) except for the Haar wavelet.
- The regularity increase with order. When N becomes very large, ψ and φ belong to $C^{\mu N}$where $\mu \approx 0.2$. This value μN is too pessimistic for relatively small orders, as it underestimates the regularity.
- The analysis is orthogonal.

Figure 4 below present the Daubechies wavelet family from db2 to db10. For different order, the signal will be decompose in different manner which gives different result.

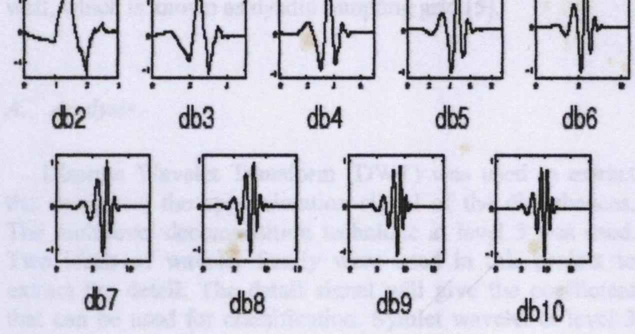

Figure 4: Daubechies Family

C. Symlets [3]

Symlets constitute a family of almost symmetric wavelets proposed by Daubechies by modifying the construction of the dbN. Properties of Symlets are similar to Daubechies except that the wavelet is symmetry. The idea of construction consists of re-using m_0 function introduced for dbN, considering $|m_0(\omega)|^2$ as a function W of the variable,$(z) = U(z)\overline{U(z^{-1})}$, since the roots of W with module different from 1 go in pairs: if z^{-1} is also a root. By constructing U so that its root is all of module < 1, the Daubechies wavelets dbN were constructed. Filter U has a minimal phase. Produces much more symmetric

filters that are the Symlet in order for the filter to have an almost linear phase, attained by optimizing factorization.
Figure below shows the Symlets of order 2 to 8. Sym1 is simply the Haar wavelet.

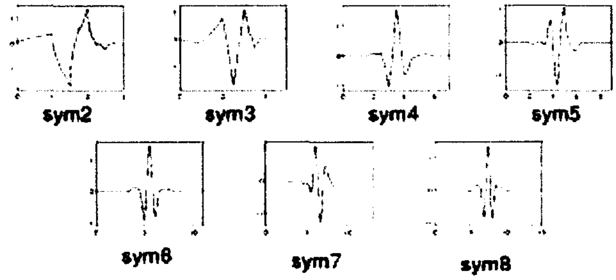

Figure 5: Symlet Family

III. DISCRETE WAVELET TRANSFORM

The discrete wavelet transform (DWT) is a form of wavelet transform that moves a time domain discretized signal into its corresponding wavelet domain. It involves a process called "sub-band codification", which is done through digital filter techniques. In the signal processing theory, to filter a given signal f(n) means to make a convolution of this signal. The *x(n)* signal is passed through a low-pass digital filter *(h(n))* and a high-pass digital filter *(g(n))*. After that, half of the signal samples are eliminated. Figure 6 below shows the sub-band codification of a signal.

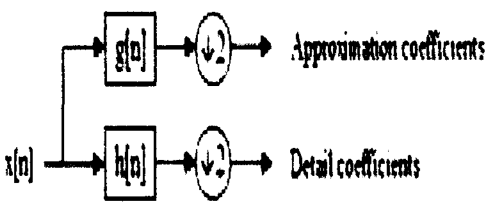

Figure 6: Sub-band Codification of Signal

There is only a single wavelet involved in time continuous time, whereas there are three different iterated filters in the discrete-time case. The process leading to discrete-time wavelet series is described as follow; consider a two channel orthogonal filter bank with filters, $h_0[n]$, $h_1[n]$, $g_0[n]$, $g_1[n]$, where $h_i[n] = g_i[-n]$. The input signal can be written as Equation (1)

$$x[n] = \sum_{k\in Z} X^{(1)}[2k+1]\, g_1^{(1)}[n-2^1k] + \sum_{k\in Z} X^{(1)}[2k]\, g_0^{(1)}[n-2k], \qquad (1)$$

In discrete-time wavelet series, the lowpass channel is split by lowpass or highpass filtering and downsampling. This lead us to the unchanged of Equation (1) on the right, while the second is expressed as Equation 2

$$\sum_{k\in Z} X^{(1)}[2k]\, h_0^{(1)}[2^1k-n] = \sum_{k\in Z} X^{(2)}[2k+1]\, g_1^{(1)}[n-2^2k] + \sum_{k\in Z} X^{(2)}[2k]\, g_0^{(2)}[n-2^2k], \qquad (2)$$

The basis functions $g^{(i)}[n]$ are defined in the time-domain version as follows;

For $g_0^{(2)}[n]$
$$G_0^{(2)}(z) = G_0(z)\, G_0(z^2) \qquad (3)$$

For $g_1^{(2)}[n]$
$$G_1^{(2)}(z) = G_0(z)\, G_1(z^2) \qquad (4)$$

From the relationship of Equation (1) and Equation (2), the input signal $x[n]$ can be expressed as Equation (5)

$$x[n] = \sum_{k\in Z} X^{(1)}[2k+1]\, g_1^{(1)}[n-2^1k] + \sum_{k\in Z} X^{(2)}[2k+1]\, g_1^{(1)}[n-2^2k] + \sum_{k\in Z} X^{(2)}[2k]\, g_0^{(2)}[n-2^2k], \qquad (5)$$

For a repeating process of J times in Equation (5), the expression becomes as follow;

$$x[n] = \sum_{j=1}^{J} \sum_{k\in Z} X^{(j)}[2k+1]\, g_1^{(j)}[n-2^jk] + \sum_{k\in Z} X^{(J)}[2k]\, g_0^{(J)}[n-2^Jk], \qquad (6)$$

In discrete-time wavelet series, special sampling is used. Each subsequent channel is downsampled by 2 with respect to the previous one and has a bandwidth that is reduced by 2 as well, which is known as dyadic sampling grid [5].

A. *Analysis*

Discrete Wavelet Transform (DWT) was used to extract the detail and the approximation signal of the disturbances. The multilevel decomposition technique at level 3 was used. Two kinds of wavelet family were used in this project to extract the detail. The detail signal will give the coefficient that can be used for classification. Symlet wavelet at level 3 (symlet3) was used to extract the detail and approximation signal of the disturbances.

Then, the detail signal from level 1 (D1) was chosen because the signal is more suitable. After that, the signal will be absolute to make the classification easier.

Another multilevel of decomposition was made using Daubechies wavelet (db3) to extract the absolute D1 signal. This is because the signal are not simplified enough to do the classification.

Again graph D1 was chosen to be analyzed since it is more suitable to be calculated. From the graph obtained, calculation will be made using the data that had been plotted.

For voltage sag disturbances, the calculation was done using the criteria of voltage drop within 0.1 to 0.9 per unit. While for voltage swell disturbances, the calculation done was using the increase of voltage within 1.1 to 1.8 per unit. The notch disturbance was classified if it occurs only in a short duration that is less than 0.5 cycles. Transient disturbances have the same criteria as notch except that it occurs in shorter duration.

Below is the flowchart of wavelet transform classification technique:

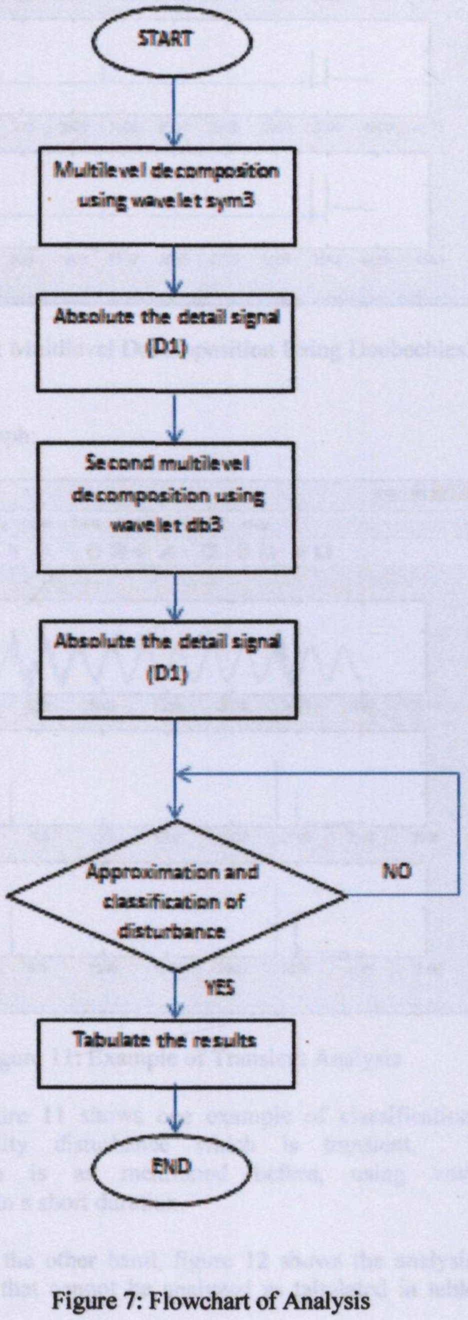

Figure 7: Flowchart of Analysis

IV. RESULTS

The method of analyzing signal is by calculating the per unit voltage drop of the signal. The figures below are examples of the analyzed signals.

Figure 8 shows the analyzed data by multilevel decomposition technique using sylmet wavelet at level 3 (sym3). The first graph shows the original signal. Second graph is the result of approximation signal (A3). The other three graphs represent the detail signal D1, D2 and D3.

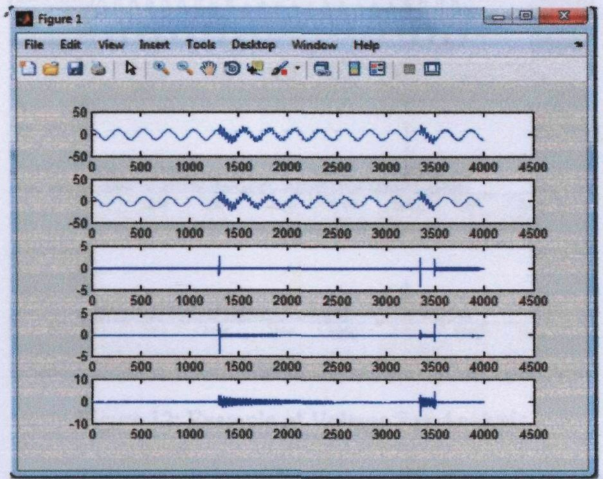

Figure 8: Multilevel Decomposition Using Symlet3

Detail signal D1 was chosen to be analysed because the signal is more suitable. The signal D1 was absolute to get a simpler calculation. Absolute D1 was shown in figure 9 below:

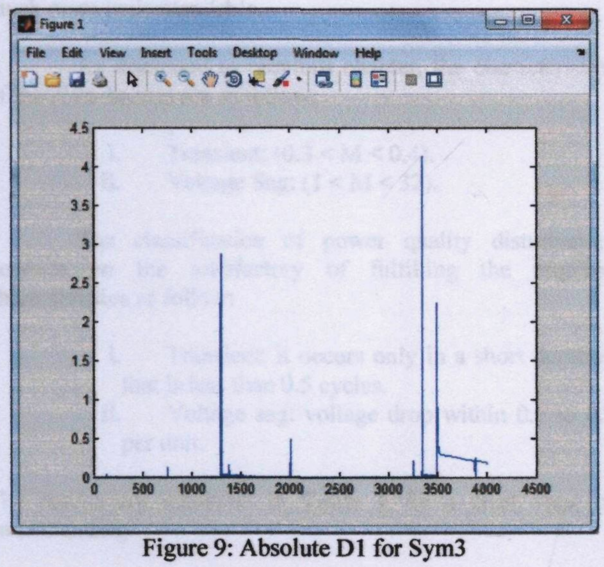

Figure 9: Absolute D1 for Sym3

Since the detail signal D1 was not simplified enough to be analyzed, another multilevel decomposition method was used to analyzed the signal. This time, daubechies wavelet at level 3 (db3) was used. The result of the decomposition is shown in figure 10:

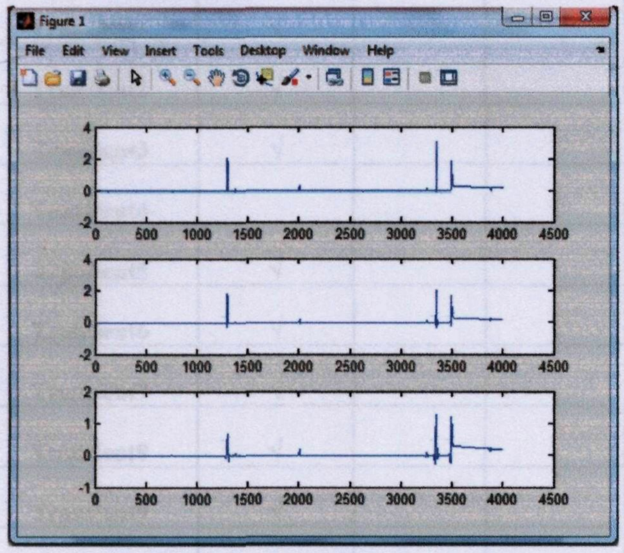

Figure 10: Multilevel Decomposition Using Daubechies3

Transient graph:

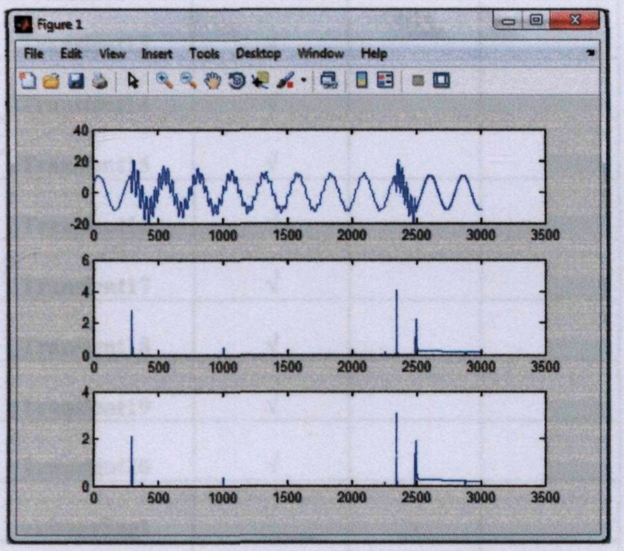

Figure 11: Example of Transient Analysis

Figure 11 shows one example of classification of power quality disturbance which is transient. The classification is as mentioned before, using voltage comparison in a short duration.

On the other hand, figure 12 shows the analysis of voltage sag that cannot be analyzed as tabulated in table 1. This may due to the criteria of disturbance which did not met the specification of the analysis. The voltage sag must have the criteria of voltage drop between 0.1 to 0.9 per unit in order to allow the system recognize the disturbance.

Voltage Sag graph:

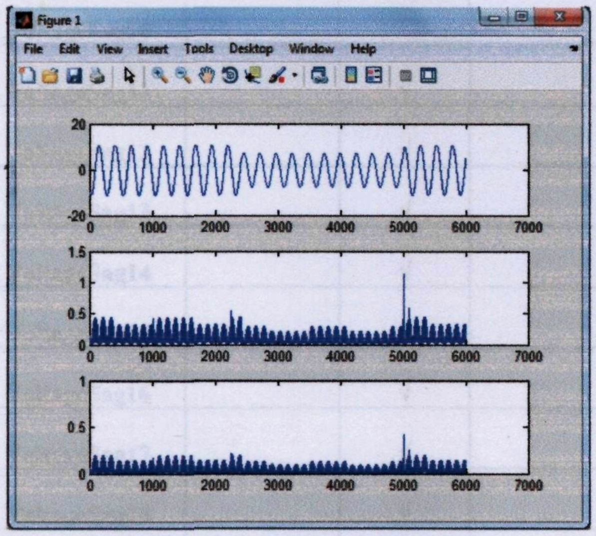

Figure 12: Example of Voltage Sag Analysis

The analysis provides the classification of transient and voltage sag disturbances. Since there are a lot of signal data that needs to be analyzed and decompose using Wavelet Transform, the signal data is being analyzed one by one at a specific equal range. This is to make sure that the Wavelet decomposition will enable to generate the signal and produce equal range of output. The classification process will also be much more understandable.

As discussed in previous chapter, the characteristics of the disturbances are as follow:

i. Transient: $(0.3 < M < 0.4)$.
ii. Voltage Sag: $(1 < M < 32)$.

The classification of power quality disturbances depends on the satisfactory of fulfilling the required characteristics as follow:

i. Transient: it occurs only in a short duration that is less than 0.5 cycles.
ii. Voltage sag: voltage drop within 0.1 to 0.9 per unit.

The results are tabulated in **Table 1** for a clear view of understanding.

Type of disturbance Signal data	Transient	Voltage Sag	Undefined
Transient1	√		
Transient2	√		
Transient3	√		
Transient4			√
Transient5	√		
Transient6	√		
Transient7	√		
Transient8	√		
Transient9	√		
Transient10			√
Transient11			√
Transient12	√		
Transient13	√		
Transient14	√		
Transient15	√		
Transient16	√		
Transient17	√		
Transient18	√		
Transient19	√		
Transient20	√		
VoltageSag1		√	
VoltageSag2		√	
VoltageSag3		√	
VoltageSag4		√	
VoltageSag5		√	
VoltageSag6		√	
VoltageSag7			√
VoltageSag8		√	
VoltageSag9		√	
VoltageSag10			√
VoltageSag11		√	
VoltageSag12		√	
VoltageSag13		√	
VoltageSag14		√	
VoltageSag15		√	
VoltageSag16		√	
VoltageSag17		√	
VoltageSag18		√	
VoltageSag19		√	
VoltageSag20		√	

Table 1: Results of Analysis

CONCLUSION

The wavelet decomposition technique has been introduced in this project as one of the method to classify power quality disturbance. Extraction of the important coefficient was done using discrete wavelet transform by using the symlet and the daubechies mother wavelet. Combination of both wavelet families proves that the wavelet analysis technique is a suitable technique to recognize and classify the power quality disturbances in electrical system.

For future development, this project can recognize harmonics disturbance. Also implement new method for classification of power quality disturbance using other technique such as Fuzzy Logic or S-transform technique.

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