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Detection of Voltage Sag and Voltage Swell in Power Quality Using Wavelet Transforms

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Abstract**—**Voltage sag, voltage swell, high-frequency noise and voltage transients are kinds of disturbances in power quality. They are also known as power quality events. Equipment used in the industry nowadays has become more sensitive to these events with the increasing complexity of equipment. This leads to the importance of distributing clean power quality to the consumer. To provide better service, the best analysis on power quality is very vital. Thus, this paper presents the events detection focusing on voltage sag and swell. The method is developed by applying time domain signal analysis using wavelet transform approach in MATLAB. Four types of mother wavelet namely Haar, Dmey, Daubechies, and Symlet are used to detect the events. This project analyzed real interrupted signal obtained from 22 kV transmission line in Skudai, Johor Bahru, Malaysia. The signals will be decomposed through the wavelet mothers. The best mother is the one that is capable to detect the time location of the event accurately.

Keywords**—**Power quality, voltage sag, voltage swell, wavelet transform.

I. Introduction

ELECTRIC utilities control voltage levels and quality but they are unable to control current [1]. It can be concluded that power quality is equal to voltage quality. Thus, to investigate voltage quality in a power system, it is adequate by focusing on analyzing voltage sag and voltage swell occur in the system. Obviously, before analyzing any power quality disturbance, a very important process is the detection. Accurate detection of undesired transient disturbances is very vital.

Wavelet transforms are mathematic tools which can be exercised in the detection of transient events. They have been developed since many years back and are very useful tools to solve frequency-dependent problems in many areas. The main advantage of wavelet transforms over the traditional Fourier transforms is its ability to identify the locations containing observed frequency content. Wavelet decomposition also allows a signal to be analyzed at different resolution levels. For a broad range of real-world signals, a discrete wavelet transform (DWT) is capable to provide a very efficient representation [2].

II. Voltage Sag

Voltage sag is the most common disturbance and very important aspect of power quality. Depending on the source of the system faults, it can occur randomly and this makes it really hard to predict [1]. In IEEE Standard 1159-1995, IEEE Recommended Practice for Monitoring Electric Power Quality, voltage sag was defined as a reduction in the RMS voltage. This event normally occurs at the power frequency between 0.1 pu and 0.9 pu for between half cycle and one minute [3]. Fig. 1 shows voltage sag signal obtained from a 22 kV transmission line, which later is to be analyzed.

III. Voltage Swell

According to the IEEE Standard 1159-1995, the IEEE Recommended Practice for Monitoring Electric Power Quality, a voltage or current swell is an increase in the RMS value between 1.1 pu and 1.8 pu at the power frequency. It can happen in durations less than one minute [3]. Swell is commonly caused by system fault conditions, switching off a large load or energizing a large capacitor bank [1]. But it is less common compared to voltage sag. On the normal phases, it also can occur during a single line-to-ground fault (SLGF) with a temporary voltage rise. Its characteristics are described by both of the magnitude and duration. Fig. 2 shows the voltage swell signal which is also obtained from 22 kV transmission line.

IV. The DWT

The DWT is a unique wavelet transform that is capable to provide a compact representation of a signal in terms of frequency and time [4]. It can be computed efficiently by successive low pass and high pass filtering of the discrete time-domain. The DWT is calculated based on two fundamental equations: The scaling function ϕ(t) and the wavelet function ψ (t), where:

$$\phi(t) = \sqrt{2}\sum_k h_k\, \phi(2t-k)$$

$$\psi(t) = \sqrt{2}\sum_k g_k\, \psi(2t-k)$$

These functions are two-scale difference equations based on a chosen mother wavelet, with properties that satisfy the conditions:

$$\sum_{k-1}^{N} h_k = \sqrt{2}$$

$$\sum_{k-1}^{N} h_k\, h_{k+2l} = 1 \; if \; l = 0 \; = 0 \; if \; l \in Z, l \neq 0$$

The discrete sequences h_k and g_k represent discrete filters that solve each equation, where N is the sampling number and

$$g_k = (-1)^{\mathrm{k}}\, h_{N-1-k}.$$

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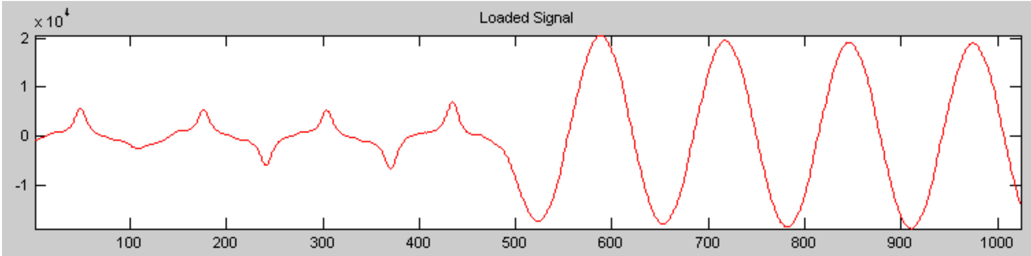


Fig. 1 Voltage sag

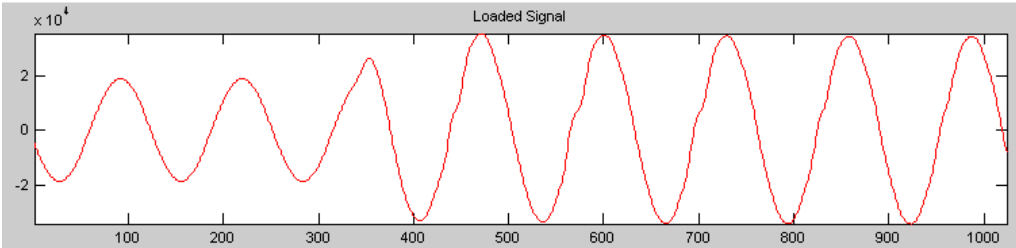


Fig. 2 Voltage swell

Orthonormal basis functions come in a few classes. The scaling and wavelet functions are the prototype of a class for the following form:

$$\phi_{j,k}(t) = 2^{\frac{j}{2}}\,\phi(\,2^{j}t - k);\; j,k \in Z$$

$$\psi_{\,j,k}(t) = 2^{\frac{j}{2}}\,\psi(\,2^{j}t - k);\; j,k \in Z$$

Z is set of integers for j and k. The purpose of parameter j is to control the dilation or compression of the function in scale of time and amplitude. While the translation of the function in time, will be controlled by parameter k.

V. Multi-Resolution Analysis Decomposition

There is an algorithm with a capability to decompose an original signal into several other signals with different levels of resolution. It is called the multi resolution analysis (MRA) algorithm. When the original signal is decomposed, approximation coefficients and detailed coefficients are obtained. A filter bank with low and high pass filter is needed to excerpt details and approximations from the original signals. The low pass filter will remove high frequency components and the high pass filter will pick out the high frequency contents in the signal being analyzed. DWT uses the scaling function ϕ (t), and the wavelet function ψ (t), to perform simultaneously the MRA decomposition of a measured signal. From the decomposed signal, the original time domain signal can be recovered without losing any information. The recursive mathematical representation of the MRA is as:

$$V_j = W_{j+1} \oplus V_{j+1} = W_{j+1} \oplus W_{j+2} \oplus \ldots \oplus W_{j+n} \oplus V_{j+n}$$

where V_{j+1} is the approximated version of the given signal at scale j+1, W_{j+1} is the detailed version that displays all transient phenomena of the given signal at scale *j+1*, $\oplus$ denotes a summation of two decomposed signals, *n* is the decomposition level.

MRA will find the average features and the details of the signal. The concept used is via the scalar products with scaling signals and wavelets [5]. Every mother wavelet functions such as Haar, Dmey, Daubechies, and Symlet are different to each other depending on the characteristic of the wavelet.

VI. Mother Wavelet Functions

The very first known and the simplest wavelet is Haar and it is similar to Daubechies, Db1 [6]. Fig. 3 shows the characteristic as discontinuous step function. It has asymmetric, orthogonal, biorthogonal properties of decomposition.

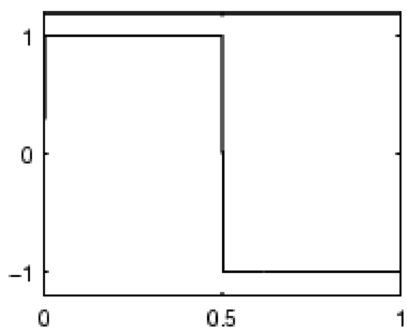


Fig. 3 Characteristic of mother wavelet Haar

Dmey wavelet is a Finite Impulse Response (FIR). By applying DWT, it allows fast wavelet coefficients calculation. Its properties are symmetric, orthogonal and biorthogonal. The Dmey wavelet characteristic can be seen in Fig. 4.

Except for Db1, Daubechies wavelets have no explicit expression. Their properties are exactly the same with Haar. Daubechies introduces modifications of the wavelets that increase their symmetry and yet retain their simplicity. Here in Fig. 5 are the wavelet functions of the three members of the family which are presented in this paper.

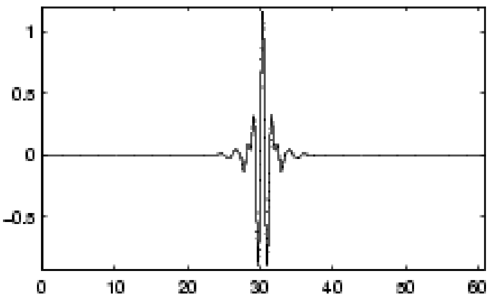


Fig. 4 Characteristic of mother wavelet Dmey

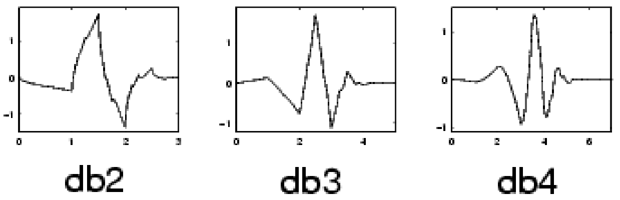


Fig. 5 Characteristic of mother wavelet Daubechies

The properties of the Daubechies and Symlet wavelet families are similar. This is because Symlets are modifications to the Daubechies family. Yet, Symlets are more symmetrical. For Symlets, this paper presents three members of the family, as shown in Fig. 6.

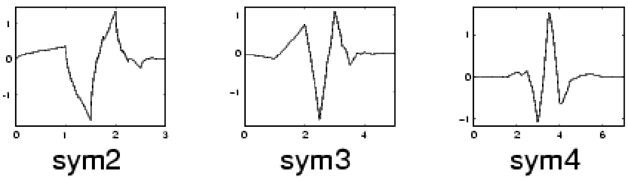


Fig. 6 Characteristic of mother wavelet Symlets

VII. Literature Review

In 2010, Lachman et al. conducted a procedure of software-based approach techniques for detection of power disturbances by time and frequency analysis with wavelet transform. The purpose is to provide a promising tool in detecting power quality problems. They generate several disturbances including notch, harmonic, interharmonic and DC offset noise. To get sufficient information, they used Daubechies 4 wavelet up to level six. Their procedures showed that the accuracy of disturbance time localization decreases as scale increases. They obtained that time detection of disturbances more accurate at lower scales and frequency at high scales. It was concluded that the use of scaling makes detection of power disturbances easier and essential in the detection process is the choice of appropriate mother wavelet [7].

Haar and Daubechies 4 are chosen by Gonzalez and Moreno from University of Cordoba as the mother wavelet in analyzing voltage disturbances. They were applied to detect and localize disturbances in voltage waveform. Frequency variations, slow and fast voltage variations, flicker, sags, swells and harmonics were developed by using MATLAB. In order to detect the disturbances, they applied the first level of decomposition for both wavelets. Only then, they found that Daubechies 4 is better than Haar in determining the time in which the disturbance appears and disappears [8].

Sushama and Tulasi from Hyderabad, India proposed two prominent methods for detection and classification of power quality disturbance. The first method is based on adaptive decomposition signal and the second method is based on wavelet transform. The proposed scheme is implemented using MATLAB. They considered voltage swell for comparing both approaches. By using statistical analysis of adaptive decomposition signal and Daubechies 4 wavelets with four levels of decomposition, they successfully proved that both methods can effectively detect any type of power quality disturbances at a faster rate [9].

In August 2007, Ying et al. from North China developed an efficient approach which is capable to detect and identify different disturbances in high accuracy and rapid speed. Wavelet decomposition is used for extracting the features of various disturbances. Then, decision tree method was used for classifying the disturbances. Voltage interrupt, swell, sag, and harmonics are generated in simulation experiment to show the effectiveness of proposed method. For online application, sliding window model and one-pass scan algorithms for wavelet decompositions are used [10].

Electrical Engineering professors, Chandrasekar and Kamaraj proposed a fresh method for detecting and classifying power disturbances. They used modified wavelet transform (MWT) for detection process and artificial neural network (ANN) to classify the disturbances. The proposed method is proven to provide better detection for both low and high frequency disturbances at different levels of noise. Besides, the combination of MWT and ANN developed a powerful tool for detection ad classification of power disturbances in all conditions and all types of transmission lines [11].

Sharmeela et al. from University of Anna, Chennai presented a procedure to detect and classify power quality disturbances using wavelets. They applied various types of wavelets and 8th level of decomposition each for a particular class of disturbances. Wavelets used are Haar, Bior, Coif, Sym5, DMeyer and Daubechies. Qualitatively compared, the results show the advantages and drawbacks of each wavelet when applied to detect the disturbances. Obtained that, Db3 detects transients, Db10 and Sym8 detect voltage flicker, Dmey detects harmonics and Db4 detects voltage Sag/Swell accurately. This procedure was tested for a large class of test conditions simulated in MATLAB [12].

In this study, Haar, Dmey, Daubechies and Symlet will be exercised as mother wavelets. While for the level of decomposition, decided that level 5 is sufficient to be applied. Most of the works in previous studies were implemented using simulated source signal of disturbance events. To make it more reliable, a real sample data recorded from 22 kV transmission line in Skudai, Johor Bahru will be analyzed.

VIII. Methodology

Applied as an original real sample data, the interrupted signals were recorded using Reliable Power Meter (RPM) equipment at 22 kV of transmission line in Skudai, Johor Bahru on February 2, 2001. Then, the obtained data displayed into CBEMA curve in RPM, as shown in Fig. 7.

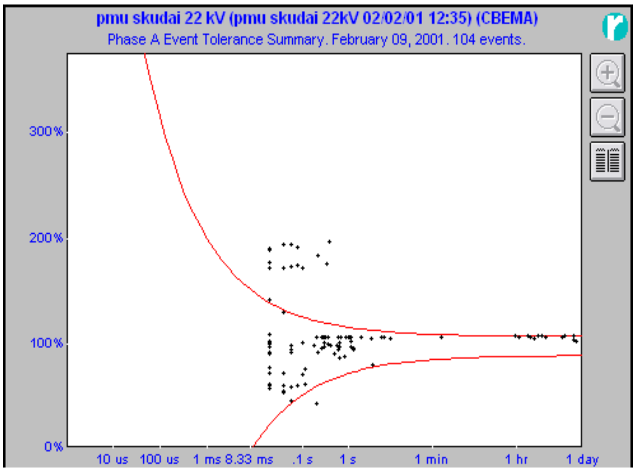


Fig. 7 CBEMA curve

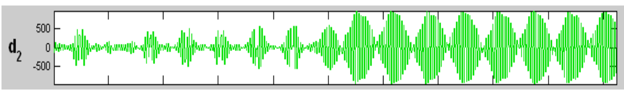
Events at the upper boundary of the curve are over voltage events where we can find voltage swell. On the contrary, voltage sag can be found at the lower side of the boundary where there are under voltage events occurred. Over voltage and under voltage events data were extracted into Excel which to be plotted in MATLAB workspace.

Then the plotted signal will be decomposed using the four wavelet mothers which have been mentioned before. To find out the accuracy for every mother wavelet in voltage sag and swell detection, time location for signal peaks from the original signals were compared to the signal peaks that had changed abruptly after the decomposition process. Only four adjacent peaks will take into account.

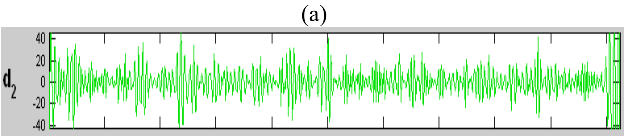
IX. Results

The interrupted signals were decomposed until level five for every mother. Among those levels, observed that level 2 gives the best view to compare the accuracy of all the wavelet mothers.

Fig. 8 shows the results for level 2 from decomposition process of real voltage sag signal as shown in Fig. 1.



(a)



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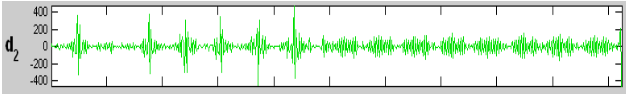

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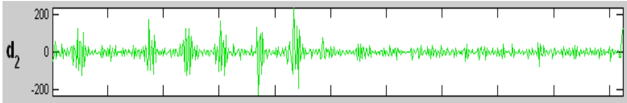
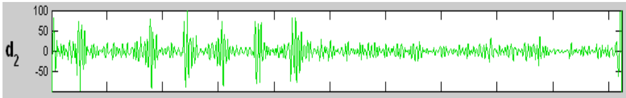
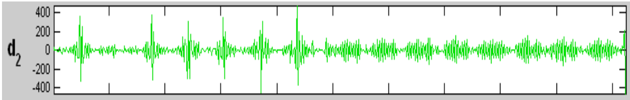


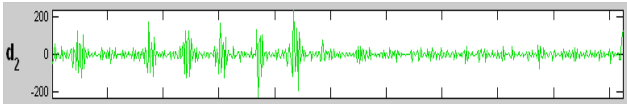
(d)



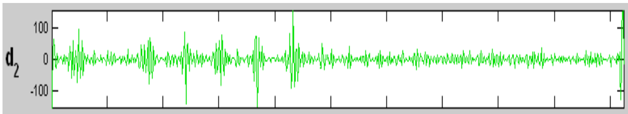
(e)



(f)



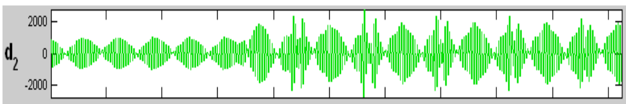
(g)



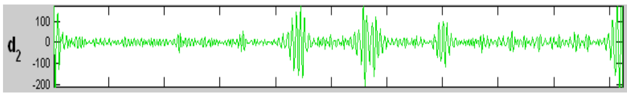
(h)

Fig. 8 Detail coefficient of level 2 decomposition signals for voltage sag obtained from mother wavelet (a) Haar, (b) Dmey (c) Daubechies 2, (d) Daubechies 3, (e) Daubechies 4, (f) Symlet 2, (g) Symlet 3, (h) Symlet 4

The decomposition process is repeated for the real voltage swell signal as shown in Fig. 2. The following are the results for level 2 from the decomposition process.



(a)



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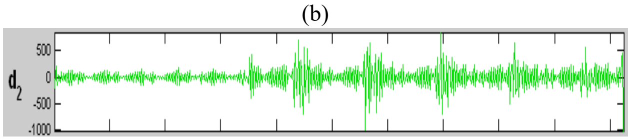

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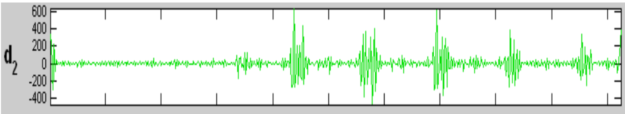

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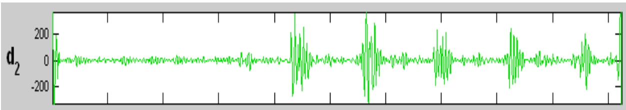
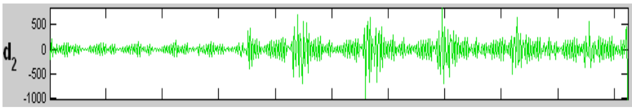
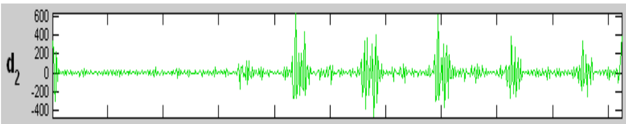


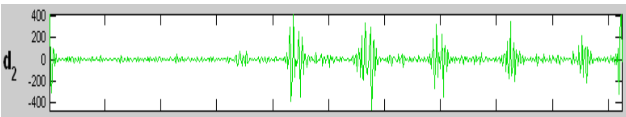
(e)



(f)



(g)



(h)

Fig. 9 Detail coefficient of level 2 decomposition signals for voltage swell obtained from mother wavelet (a) Haar, (b) Dmey (c) Daubechies 2, (d) Daubechies 3, (e) Daubechies 4, (f) Symlet 2, (g) Symlet 3, (h) Symlet 4

Referring to the original voltage sag signal, as shown in Fig. 1, the event occurred half of the sample signal on the left. The other half on the right is smooth signal. The x-axis represents time location for the signal and the same goes to Figs. 8 and 9. In Fig. 8, all the signals (a) until (h) have an abrupt change of signal peak every time the event occurred as observed on the half left side of the signal. While, in the real sample of voltage swell signal in Fig. 2, the event occurred on the half right side of the signal and the other half is smooth signal. Again, in Fig. 9, all the signal peaks in (a) until (h) changed abruptly every time the event occurred as observed on the half right side of the signal. Therefore, it was assumed that the significant changes are the time location for the disturbances occurred.

For voltage sag event, time location for signal peaks were obtained from Fig. 1 and time location for the decomposed signal peaks were obtained from Fig. 8. As mentioned before, only four adjacent peaks are taken into account. All the data were recorded in Table I.

While for voltage swell event, time location for signal peaks were obtained from Fig. 2 and time location for the decomposed signal peaks were obtained from Fig. 9. All the data were recorded in Table II.

TABLE I
TIME LOCATION FOR ORIGINAL VOLTAGE SAG SIGNAL PEAKS AND DECOMPOSED SIGNAL PEAKS FOR EACH MOTHER WAVELET

Signal	Time location fault (µs)			
	1st peak	2nd peak	3rd peak	4th peak
Original voltage sag event	47.57	176.50	303.70	433.70
HAAR	43.62	172.20	297.90	438.00
DMEY	48.00	170.70	297.90	440.00
DB2	48.00	176.00	304.00	435.90
DB3	46.00	174.00	302.00	434.00
DB4	50.10	178.00	306.00	432.90
SYM2	48.00	175.90	303.90	436.00
SYM3	46.00	173.90	302.00	434.00
SYM4	49.00	177.00	304.90	433.00

TABLE II
TIME LOCATION FOR ORIGINAL VOLTAGE SWELL SIGNAL PEAKS AND DECOMPOSED SIGNAL PEAKS FOR EACH MOTHER WAVELET

Signal	Time location fault(µs)			
	1st peak	2nd peak	3rd peak	4th peak
Original voltage swell event	471.30	600.00	729.90	858.50
HAAR	435.10	562.30	690.90	823.80
DMEY	444.90	558.00	701.00	824.90
DB2	440.00	568.00	696.00	828.00
DB3	437.90	581.90	693.90	826.00
DB4	436.90	565.00	693.00	825.00
SYM2	440.00	567.90	695.90	827.90
SYM3	438.00	581.90	694.00	825.90
SYM4	436.90	564.90	692.90	824.90

TABLE III
VOLTAGE SAG.: PERCENTAGE DIFFERENCE OF THE TIME LOCATIONS BETWEEN THE SIGNAL PEAKS OF THE DECOMPOSED AND THE ORIGINAL SIGNAL

Mother wavelet	Percentage of difference (%)				Average of percentage of difference (%)
	1st peak	2nd peak	3rd peak	4th peak	
HAAR	8.30	2.44	1.91	0.99	3.41
DMEY	0.90	3.29	1.91	1.45	1.89
DB2	0.90	0.28	0.10	0.51	0.45
DB3	3.30	1.42	0.56	0.07	1.34
DB4	5.32	0.85	0.76	0.18	1.78
SYM2	0.90	0.34	0.07	0.53	0.46
SYM3	3.30	1.47	0.56	0.07	1.35
SYM4	3.01	0.28	0.40	0.16	0.96

TABLE IV
VOLTAGE SWELL: PERCENTAGE DIFFERENCE OF THE TIME LOCATIONS BETWEEN THE SIGNAL PEAKS OF THE DECOMPOSED AND THE ORIGINAL SIGNAL

Mother wavelet	Percentage of difference (%)				Average of percentage of difference (%)
	1st peak	2nd peak	3rd peak	4th peak	
HAAR	7.68	6.28	5.34	4.04	5.84
DMEY	5.60	7.00	3.96	3.91	5.12
DB2	6.64	5.33	4.64	3.55	5.04
DB3	7.09	3.02	4.93	3.79	4.71
DB4	7.30	5.83	5.06	3.90	5.52
SYM2	6.64	5.35	4.66	3.56	5.05
SYM3	7.07	3.02	4.92	3.80	4.70
SYM4	7.30	5.85	5.07	3.91	5.53

Then, the time location obtained from the decomposed signal peaks were compared to the original event signal peaks in order to calculate the accuracy for each mother wavelet in detection of voltage sag and voltage swell. The differences of the time locations were recorded in percentage for voltage sag and voltage swell events in Tables III and IV, respectively.

X. Conclusion

From Table III, it can be concluded that Db2 is the most accurate mother wavelet to detect voltage sag events occurring in the 22 kV transmission line of Skudai, Johor Bahru. It is because it has 0.25%, which is the least average value of the difference between decomposed and original voltage sag signal peaks. While in Table IV, it can be observed that Sym3 is the most accurate mother wavelet for detection of voltage swell events. It gave the least value which is 4.70% of average percentage difference of time location between decomposed and original voltage swell signal peaks. Yet, all four mothers are not suitable enough to be applied in voltage swell events detection. This is because they produced large difference of time location for the events between the real voltage event signals and decomposed signal.

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