Distinguishing Micro-scale Voltage Disturbances Using Wavelet Decomposition Techniques

By

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13876

Dissertation submitted in partial fulfilment of
the requirements for the
Bachelor of Engineering (Hons)
(Electrical & Electronic)

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CERTIFICATION OF APPROVAL

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A project dissertation submitted to the
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Approved by,

____

(Dr. Sarat Chandra Dass)

UNIVERSITI TEKNOLOGI PETRONAS
TRONOH, PERAK
May 2014

CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

WAN CHEN YOONG

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LIST OF ACRONYMS

1 D	One-dimension
CWT	Continuous Wavelets Transform
DWT	Discrete Wavelet Transform
FT	Fourier Transform
MATLAB	Matrix-Laboratory
PQ	Power Quality
RMS	Root-mean-square
WT	Wavelets Transform

ABSTRACT

Power quality (PQ) issues have raised the attention of all parties especially the power electronic community as the disturbances occurred during the power transmission and distribution downgrades the service quality of the power delivered and causes damage to the connected load. In this paper, three types of PQ disturbances: voltage sag, voltage swell and voltage notch are discussed and a novel approach to distinguish various PQ signal using wavelet multi-resolution decomposition technique is proposed. Today, wavelet transform is increasingly being employed in signal processing in place of Fourier-based technique. The main reason for advocating wavelet transform is that it not only traces signal change across time plane but it also decompose the signal across the frequency plane. In this paper, Haar wavelet and 4-levels of signal decomposition are adequate to detect and distinguish the disturbances from their background. All the modelling and classification processes are performed in MATLAB where wavelet-1D toolbox and MATLAB algorithm are developed and employed. Based on the wavelet decomposition technique, voltage sag and voltage swell disturbances are identified at low frequency bands such as detail coefficients d4 and approximation coefficients a4. Conversely, voltage notch disturbances are clearly captured at high frequency bands particularly in the detail coefficients d1 and d2. 3 types of PQ disturbances are well detected and distinguished by employing this method. This approach is effective in tracking various PQ disturbances as compared to the conventional point-to-point comparison method which is principally based on visual inspection.

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CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Power Quality (PQ) is becoming prevalent especially in the power industry lately. PQ defines the fitness of the electrical power delivered form the production from the power plant to the electronic devices used by consumers. It is also known as the compatibility of the equipment connected to the grid system. However, the complexity of the power system to deliver the electrical power from the point of production to the point of consumption provides many opportunities for the quality of the power to be compromised.

There are several PQ events that are commonly occurred during the distribution of electrical power including: voltage sags, voltage swell, outages, harmonics, notches, oscillatory transient, and spikes. These PQ disturbances phenomena have raised the attentions of all due to the high usage of electronically controlled equipment such as programmable logic controller (PLC) and microprocessor. Most of these devices are quite susceptible to disturbances of the incoming power signal and the cost due to these disturbances can be substantial. Based on the figure presented by Electrical Power Research Institute (EPRI), PQ phenomena have contributed \$15 billion to \$24 billion losses in the US economy [1]. Therefore, to ensure the efficiency and life expectancy of the sensitive load equipment, a clean voltage waveform is very desirable.

In fact, PQ disturbances can be divided into two main categories namely: variations and events. Variation disturbance is happened during steady state phenomena where the signal shows small deviations from its nominal value. These disturbances include harmonics, voltage sags and voltage swells. On the other hands, events disturbance is occurred randomly during the operating process and it is normally large deviations from its normal conditions; such as interrupts and rapid transients.

In the past research, the detection and recognition of the signal disturbances is primarily based on visual inspection of the waveform by comparing point-to-point with the adjacent cycle. This approach has shown its limitation in detecting periodic disturbances, thus a more powerful method shall be proposed to improve the classification process. In this paper, three major PQ disturbances: voltage sags, voltage swells and voltage notches are distinguished by applying wavelet multi-resolution decomposition technique. Wavelet-based decomposition method has been widely used to model some short duration events or interrupts due to its flexibility in window size and its capability to present the data in time-frequency domain [3]. For this reason, wavelet transform (WT) is considered as a better tool than Fourier Transform (FT) and other methods with its additional desirable features that could pinpoint the occurrence of the PQ disturbances and the ability to process signal data across several frequency bands. Thus, in this paper, wavelet-based multi-resolution decomposition technique has been implemented to analyse and distinguish PQ disturbances.

1.2 PROBLEM STATEMENT

The damage caused by PQ disturbances is clearly visible in both public and industrial facilities as the PQ disturbances cause malfunction in the power supply and the equipment used. Voltage sag is pretty common to occur at the industrial facilities when large loads are connected to the power supply. Due to the high capacity of the connected load, the amplitude of the power supply has dropped dramatically which in return contaminating the quality of power supply. To ensure the power distribution is performed at its best condition, techniques to classify and detect the PQ disturbances are necessary and crucial.

Problem arises when the existing methods such as point-to-point comparison of adjacent cycle failed to visualise the disturbances that appear periodically. Besides, minor disturbance that occur during power distribution are barely noticeable by using the existing visual inspection method. Apart from that, Fourier Transform (FT) which is commonly applied in the signal processing shows its limitation in extracting features that characterise PQ disturbances precisely [1]. Therefore, to overcome the inadequacy of the current techniques, wavelet-based decomposition approach is proposed to improve the detection and classification of the PQ disturbance signals. Wavelet-based method is able to exhibit both time and frequency component of the disturbances signals where the disturbances can be clearly identified from the wavelet coefficients obtained. In addition, due to the capability of analysing power signal in vary window sizes; wavelet decomposition technique is well-suited for PQ analysis.

1.3 OBJECTIVES

The objectives of the project are:

i. To study three types of PQ disturbances: voltage sags, voltage swells and voltage notches

ii. Detection and classification of the PQ disturbances are based on wavelet multi-resolution decomposition technique

1.4 SCOPE OF STUDY

In this project, three types of PQ disturbances namely: voltage sags, voltage swells and voltage notches are expected to be distinguished by using wavelet multi-resolution decomposition approach.

In completing this project, few theories and concepts are introduced:

a) Types of PQ disturbances

According to the IEEE 1159 to1995, the definition of voltage sags and voltage swells based on the Recommended Practice on Monitoring Electric Power Quality are [2]:

Sag is a reduction in amplitude by means of 0.1 to 0.9pu in Roots-Mean-Square (RMS) of the power signal for duration from 0.5 cycles to 1 minute. System faults, energization of heavy loads and initiating of large motors are the major contributors for the voltage sags to occur. Whereas, swell is a raise in amplitude by means of 1.1 to 1.8pu in RMS of the power signal which last from 0.5 cycles to 1 minute.

Swells are usually caused by sudden load decreases and associates with single line-to-ground fault on the system. On the other hands, voltage notch is a type of waveform distortion where the signal is deviated from an ideal sinusoidal wave during the steady state. It is mainly due to the usage of power electronic devices such as rectifier that causes the current to fluctuate from one phase to another.

b) Wavelets multi-resolution decomposition techniques

Wavelets are defined as a function that behaves like a wave form fluctuating above and below the x-axis of the processing signal. The representation of wavelets is known as wavelets transform (WT),

it can be divided into continuous wavelets transform (CWT) and discrete wavelets transform (DWT). In this project, DWT is considered over CWT as it is more efficient computationally and require less memory storage. By applying DWT decomposition technique, power signal can be represented in the form of wavelet coefficients based on the decomposition level used. Low scale signal decomposition provides high time localization while high scale signal decomposition yields poor time localization. Thus, three or four level of decomposition is sufficient to distinguish the PQ disturbances.

CHAPTER 2

LITERATURE REVIEW

High dependence of power electronic devices which are susceptible to signal disturbances challenges the PQ in term of performance and life expectancy [4]. Wide application of non-linear, time-variant loads in the power distribution network alters the behaviour of the power and downgrades the service quality of the power supply [1]. Therefore, in order to improve the service quality of the power signal, an effective real-time monitoring system that are able to identify and classify different types of disturbances events has to be considered before any further mitigation can be conducted. However, abundance data have to be analysed which is time consuming and not effective. Thus, more efficient approach is necessary in the PQ assessments to detect and distinguish the disturbances signal [4].

In the paper [1] He *et.al* mentioned that WT approach is a powerful method to classify PQ disturbances because it provides both time and frequency information of the analysed signals. WT outshines FT in term of vary window sizes and its ability to representing the power signal in time-frequency domain. This additional feature of WT exhibits its effectiveness in tracking signal dynamics and recognising the time of occurrence of the PQ disturbances [4]. Narrower window is used at the high frequencies in order to get better time resolution; whereas at the low frequencies, wider window are preferred for better frequency resolution. For this reason, WT is further applied in the area of images and signals processing in order to extract the feature vectors based on the multi-resolution signal decomposition method proposed by Gauda *et al*. This method makes use of standard deviation and RMS value of the signal to distinguish the PQ disturbances [1]. WT is useful in localising and distinguishing various types of PQ events due to its sensitivity in tracking signal irregularities [8]. The decomposition level used in this approach reflects the resolution of the time-frequency components [8]. In other words, a high decomposition level corresponds to lower frequency where coarser feature of the signal is detected. On the contrary, a low decomposition level corresponds to higher frequency where finer feature of the signal is observed. Thus, wavelet-based classification approach possesses the advantages in term of speed and precision discrimination during transient event and voltage variations over the conventional approach [5]. Figure 1 shows an example of 4-levels wavelet decomposition, where "a" is denoted as approximation coefficients and "d" is indicated as details coefficients. Approximation coefficients are low frequency component that passes through low pass filter; whereas, details coefficients are high frequency components that undergo high pass filter. With such decomposition, the detection and localisation of the PQ disturbances can be performed precisely and effectively.

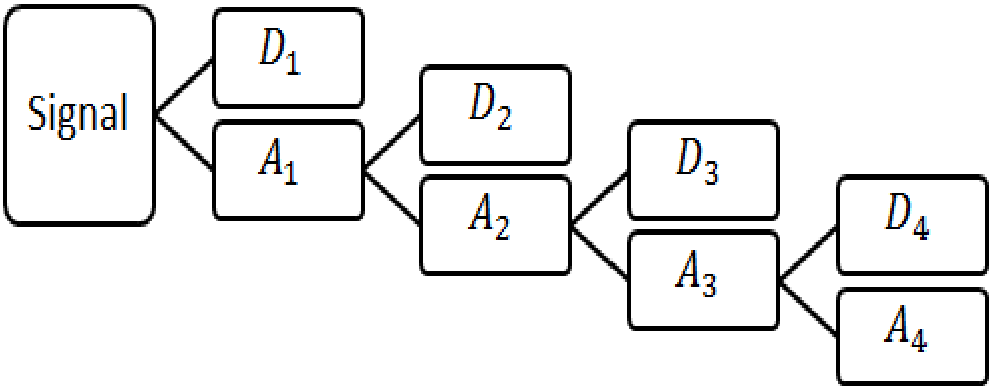

FIGURE 1: Wavelet multi-resolution 4-levels decomposition

Moreover, a type of neural network called SOLAR (self-organizing learning array) based on the wavelet multi-resolution analysis was proposed by He. *et.al* has reported high accuracy of 94.93% [6]. However, neural network shows its inadequacy in term of flexibility and feasibility as it requires specific neural network architecture to detect a particular type of PQ disturbances. As a matter of fact, the existing technique that is available in the commercial market is mainly based on a point-to-point comparison of adjacent cycles [8]. Each sample point of the present cycle is compared to the corresponding sample point of the previous cycle where the differences between the cycles are considered as the disturbances [8]. However, in this approach, periodically disturbance such as flat-top wave shape disturbance is failed to be identified. In addition, detection based on visual inspection of the power signal is limited in tracking minor disturbances and fail to indicate PQ events accurately. Another approach known as Fourier transform which is commonly used in signal processing is not suitable for disturbance detection. Fourier transform can only represent the signal in one particular frequency fails to identify the disturbances that occur at different frequencies.

In general, wavelet decomposition technique is just a series of convolution and decimation process at each corresponding scale. Dilated (stretched) and translated (shifted in time) are introduced in the wavelet function where dilation is denoted as a, while time translation is denoted as b [8]. Thus, wavelet function is simply computed by circular convolution of the signal with the wavelet function

$$W\{f(a,b)\} = < f, \Psi_{a,b} > = \int_{-\infty}^{+\infty} f(t) \cdot \frac{1}{\sqrt{a}} \Psi(\frac{t-b}{a}) dt. \quad (1)$$

Where $f(t)$ is the original signal, a is a positive real number and b is a real number and the particular version of the mother wavelet, $\Psi_{a,b}(t)$. However, the wavelet function only displays the high frequencies information when scale $a < 1$. In order to obtain the low frequency information for full representation of the original signal, $f(t)$, it is crucial to determine wavelet coefficients for scale $a > 1$. This can be achieved by introducing scaling function, $\phi(t)$ where the low frequency approximation of $f(t)$ can be computed by circular convolution [8]

$$\mathcal{L}\{f(a,b)\} = < f, \phi_{a,b} > = \int_{-\infty}^{+\infty} f(t) \cdot \frac{1}{\sqrt{a}} \phi(\frac{t-b}{a}) dt \quad (2)$$

Wavelet technique is widely applied in signal processing as compared to Fourier Analysis is mainly due to its vast choice of wavelets as the basis function.

This enables wavelet analysis to be adapted accordingly to the expected characteristic of the signal. In wavelet families, it consists of several types of wavelet such as Haar wavelets, Daubechies wavelets, Coidlets wavelets, Morlet wavelets and so on which possess their respective function and characteristic. Haar wavelet is considered over other wavelet families are due to the particularly desirable characteristic of Haar wavelets that they are zero everywhere except on a small interval [7]. Besides, Haar wavelet is the simplest representation of signal which is constantly employed for teaching and illustration purposes. Figure 2 shows the representation of Haar wavelets where Haar function is an orthonormal rectangular pair.

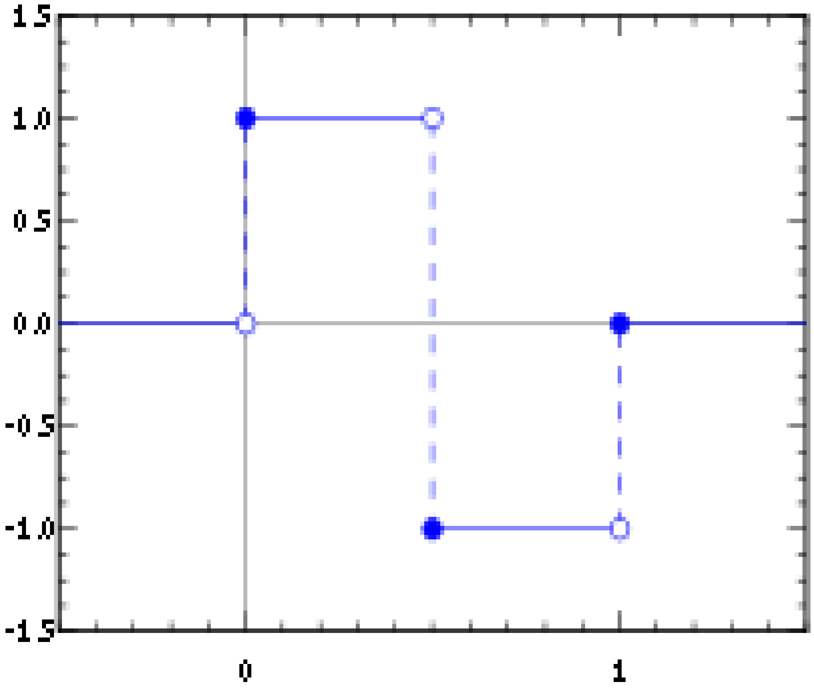

FIGURE 2: Haar Wavelet [7]

CHAPTER 3

RESEARCH METHODOLOGY

3.1 FLOW CHART OF THE PROJECT

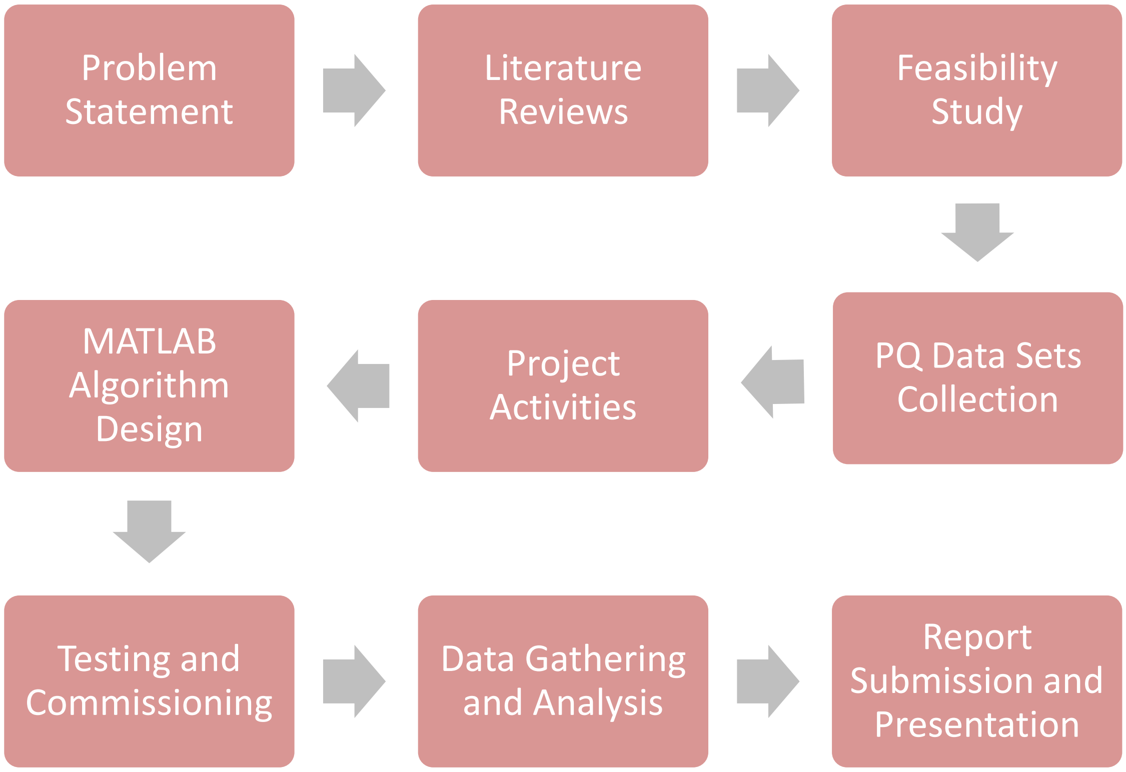

FIGURE 3: Flow chart of the Project

3.2 PROJECT ACTIVITIES

For the first phase of the project, data sets of the power signal which contains the required disturbances are gathered and collected. 50 data sets for each of the PQ disturbances are collected and analysed to ensure the accuracy of the classification process. For this reason, voltage signal are generated from the 3-phase voltage source distribution system with circuit breaker in MATLAB Simulink as shown in Figure 4.Figure 4 demonstrates the power transmission and distribution model to generate the necessary power signal for interpretation. Voltage sag, voltage swell and voltage notch signals are generated by adjusting the parameters in the 3-phase circuit breaker. The frequency applied for the disturbance signal is 50Hz and the duration of the model stimulation is 0.35 seconds (350ms). Therefore, the period of one cycle of the signal is 0.02 seconds (20ms) and about 17 cycles of the signal are generated in every power signal.

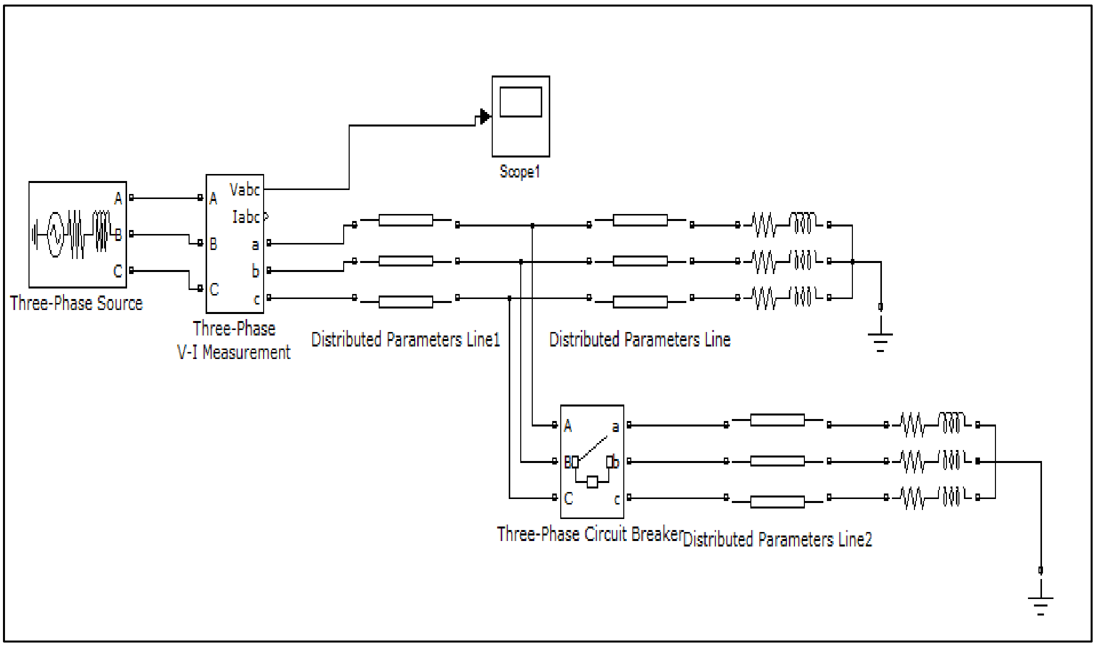

FIGURE 4: 3-phase voltage source distribution system with circuit breaker model

The obtained signals generated from the Simulink are analysed in the wavelet 1-D toolbox. Wavelet 1-D toolbox allows user to make adjustment on the decomposition level and types of wavelet family depending on the behaviour of the signals. In this paper, decomposition level is set to level 4 and Haar wavelet is chosen. Decomposition and reconstruction of the voltage signal is presented in the form of wavelet coefficients across various frequency bands. Thus, any PQ disturbances that happened in the signal can be easily captured and identified. Due to its flexibility in term of vary window sizes, voltage signals is decomposed into lower resolutions where wider window size is applied in low frequency bands to capture slow changing events while narrow window size is used in high frequency bands to detect fast transients disturbance.

Apart from that, decomposition and reconstruction of the voltage signals can be achieved by developing a MATLAB algorithm. The algorithm is able to perform multi-resolution decomposition and properly displays the desirable signal waveform. Besides, the wavelet coefficients obtained are smoothed to aid in visual identification of PQ disturbances. The MATLAB algorithm is saved in *decomposition.m* of MATLAB m-file (APPENDICES A).

3.3 KEY MILESTONES

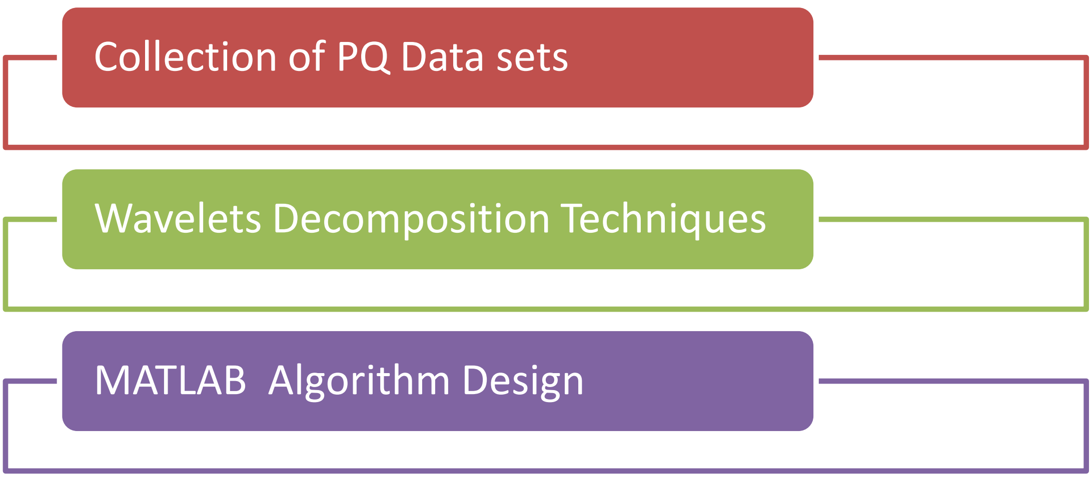

FIGURE 5: Key Milestones of the Project

Basically, the project is divided into 3 main parts as shown in Figure 5. In order to analyse the PQ disturbances, data sets or case study of the PQ have to be collected. The data sets shall be focus on three types of PQ disturbances which are voltage sags, voltage swells and voltage notches. Those data sets are necessary for further classification process. By using wavelet multi-resolution decomposition technique, the coefficients of the wavelets are obtained where the disturbances that present in the signal will clearly be identified. In this project, the decomposition and classification process of the voltage signals are performed and analysed in MATLAB. By developing an appropriate MATLAB algorithm and modelling the voltage signal in the wavelet toolbox, the desired PQ disturbances can be detected and distinguished accordingly.

3.4 GANTT CHART

TABLE 1: Gantt chart of the project

WEEK / TASK	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
Project Title Selection																												
Literature Reviews																												
Extended Proposal																												
Study on Wavelets Decomposition																												
Proposal Defence																												
Collection of PQ Data Sets																												

Interim Report Submission																												
MATLAB algorithm development																		★										
Progress Report Submission																												
Testing and Commissioning																						★						
Poster Presentation																									★			
Technical Paper Submission																												
Final viva																											★	
FYP Dissertation Submission																												

★ Key milestones

CHAPTER 4

RESULTS AND DISCUSSION

The proposed disturbance detection and classification approach that are introduced in chapter 3 is implemented in voltage sag, voltage swell and voltage notch disturbance signals. By applying 4 levels of decomposition, five frequency bands are generated where detail coefficient, *d* has the higher frequency as compared to approximation coefficients, *a*. During signal decomposition, the original signal, *s* is decomposed into lower resolutions where *d1* has the highest frequency, followed by *d2, d3, d4* and the lowest frequency band is *a4*. In the following, PQ disturbances that are occurring in the processed signal are pinpointed and highlighted.

4.1 VOLTAGE SAG DISTURBANCE

4.1.1 SEVERE SAG DISTURBANCE

Voltage sag disturbances can be identified when there is a sudden drop of voltage amplitude from its nominal value. Figure 6a shows a 47% voltage sag disturbance for 7 cycles, starting from the 6^{th} cycle to 12^{th} cycle as highlighted in the red box. The nominal value of the voltage signal is 232V but due to the fault applied at the circuit breaker, the voltage of the signal is dropped to 122V. The sag disturbance in Figure 6a is considered as severe since the reduction in voltage amplitude is exceeding 30%. Based on Figure 6a, the detection and localisation of the sag disturbance are visibly indicated in the lower frequency band which are wavelet approximation coefficients *a4* and detail coefficients *d4*. Due to the characteristic of wavelets transform, wider window size is employed in the lower frequency band (*a4* and *d4*) to trace the slow changing variations events. In other words, a low frequency band is more applicable in detecting the voltage sag disturbance.

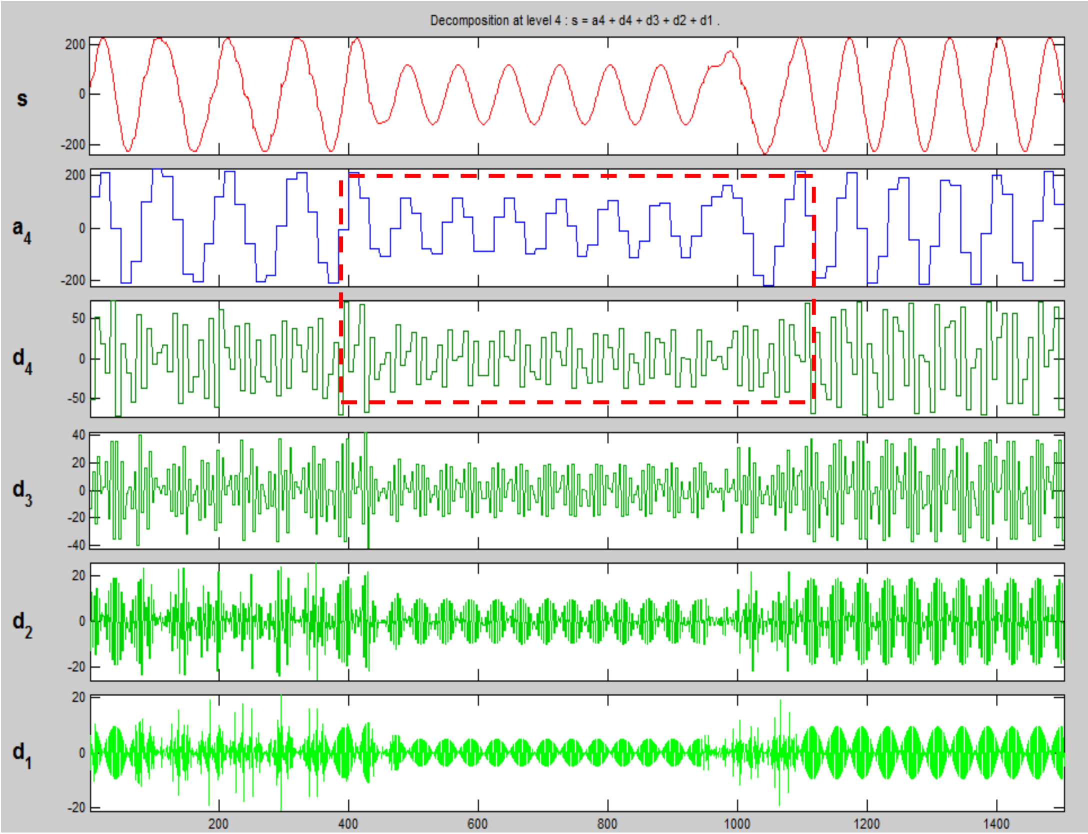

FIGURE 6a: Voltage sag disturbance (sag39.mat) at 4-scale decomposition

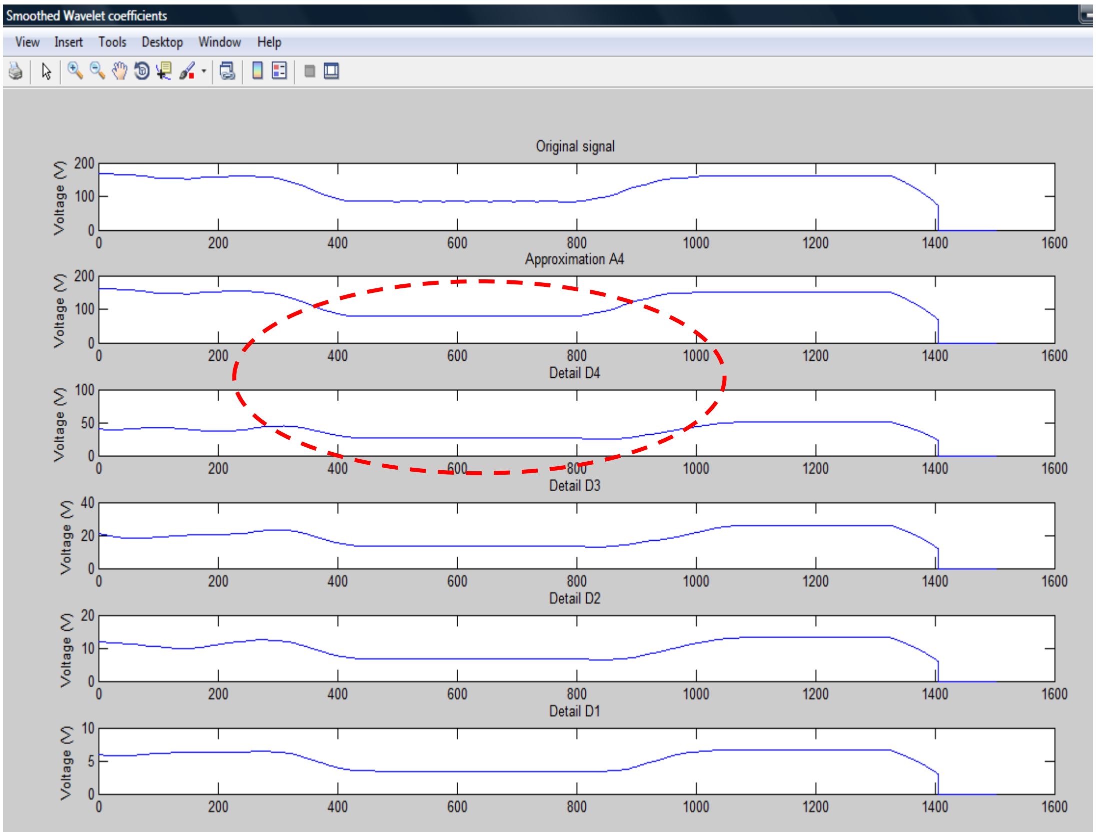

FIGURE 6b: Smoothed wavelet coefficients (sag39.mat)

To aid in signal analysis, the wavelet coefficients is smoothed in order to capture the important patterns of the disturbance signal while removing any unwanted noise or other fine-scale rapid phenomena. Figure 6b demonstrates the wavelet coefficients that have been smoothed. Small dip is noticed as highlighted by the red circle implies the occurrence of the sag disturbance. With this representation of the voltage signal, the present of sag disturbance can effortlessly be detected and noticed particularly in *a4* and *d4* coefficients.

4.1.2 MINOR SAG DISTURBANCE

Minor sag disturbance in the power signal is difficult to be detected through conventional way of visual inspection. The fall of the voltage level is minimal but it cannot be negligible. Figure 7a illustrates a minor sag disturbances signal where the amplitude of the voltage has dropped 19.5% from its nominal value. The sag disturbance is last for 3 cycles, starting from 3rd cycle to 5th cycle as highlighted in the red box. From the result obtained, approximation coefficient *a4* serves as the best frequency scale to observe and detect the sag disturbance. Higher frequency band such as detail coefficients *d1* and *d2* fail to capture the occurrence of the sag disturbance. This is because the sag disturbance in Figure 7a is pretty minor and hardly to be noticed. In other words, high frequency band such as detail coefficients *d1* and *d2* are inappropriate to capture the effect of sag disturbance. Figure 7b presents the smoothed sag disturbance signal (sag50.mat) after applying 4-level of wavelet decomposition. A slight decline in the amplitude of the signal is spotted indicates the present of voltage sag disturbance. This sag characteristic is best described in approximation coefficient *a4* which is the lowest frequency band as indicated in the red circle. Basically, wavelet coefficient *a4* is the de-noised signal of the original voltage signal after applying the low pass filter. Therefore, unwanted noise is removed which enable us to clearly visualise and detect the occurrence of sag disturbance.

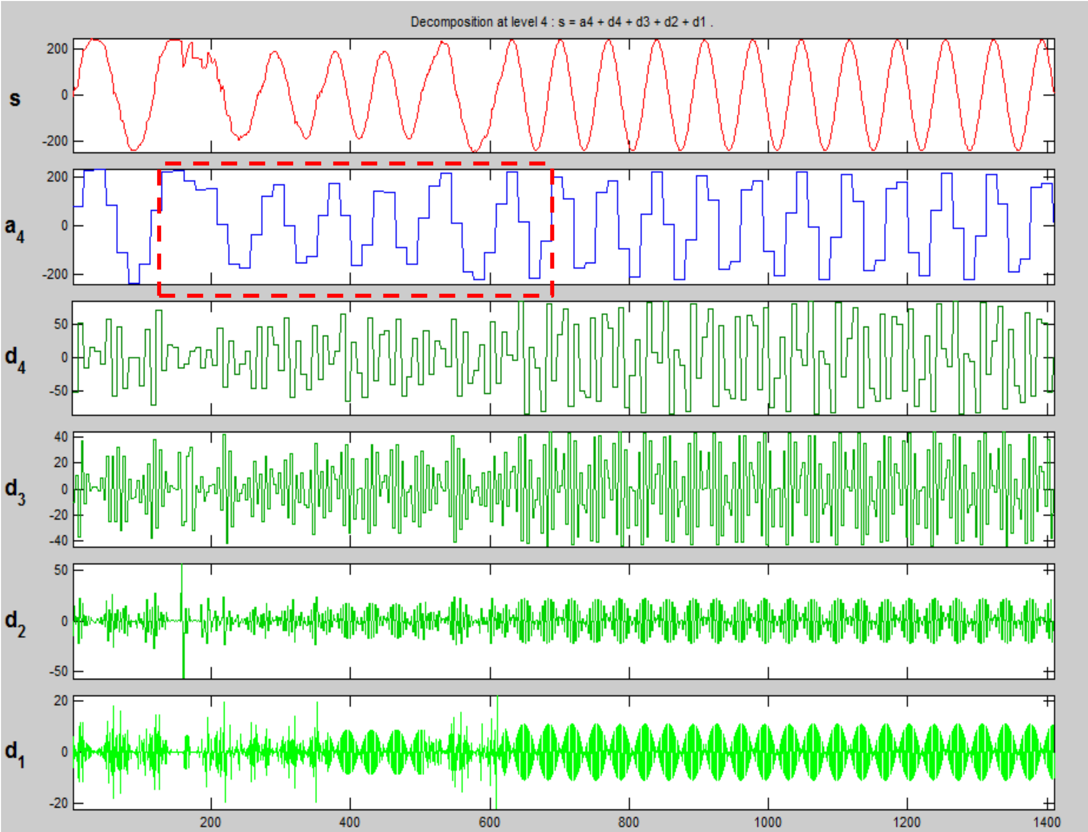

FIGURE 7a: Voltage sag disturbance (sag50.mat) at 4-scale decomposition

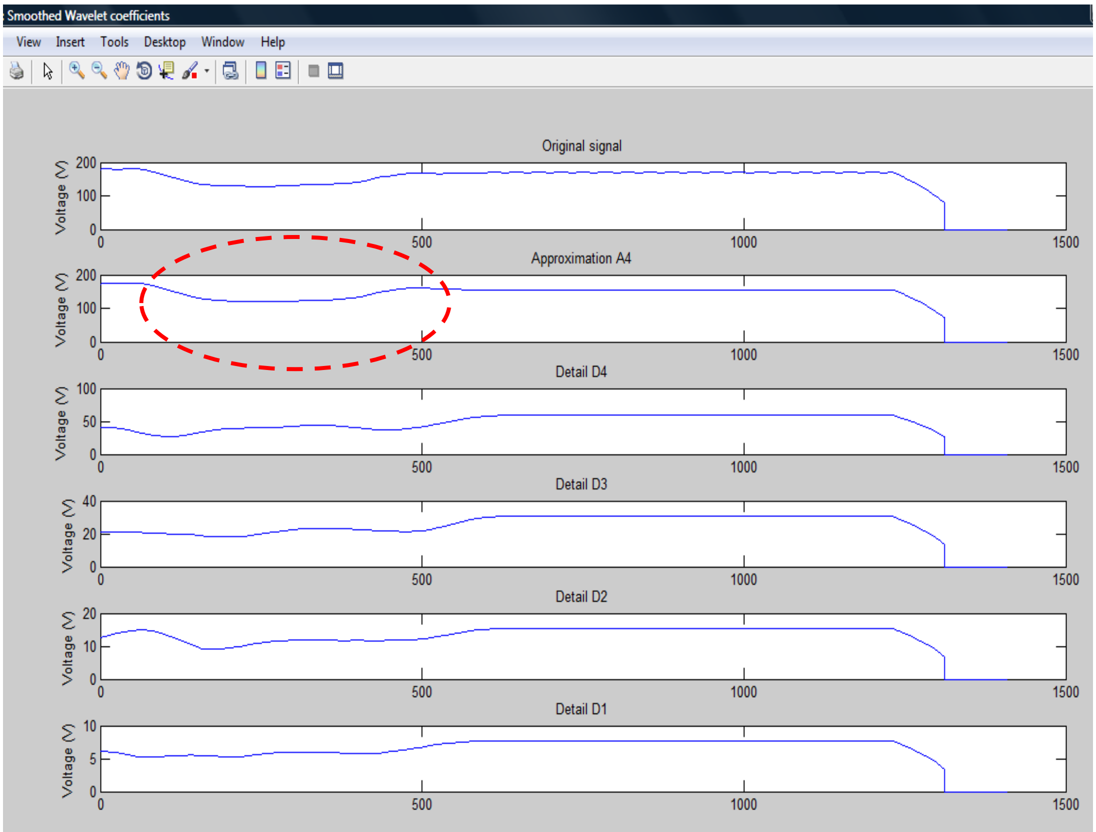

FIGURE 7b: Smoothed wavelet coefficients (sag50.mat)

4.1.3 SAG DISTURBANCE AT DIFFERENT TIME OF OCCURRENCE

Figure 8a and Figure 8b show a sag disturbance (sag21.mat) is detected at the early cycle of the voltage signal. The sag percentage is reported as 49% where the amplitude of the signal is reduced from 365V to 185V.The sag is occurring for 8 cycles from the very beginning to the 8th cycle of the voltage signal. Since the sag disturbance is quite severe thus; it is visible in all frequency bands. However, approximation coefficients *a4* and detail coefficient *d4* are preferred in tracking sag disturbance due to the wider window size is used during wavelet decomposition to trace slow changing sag disturbance.

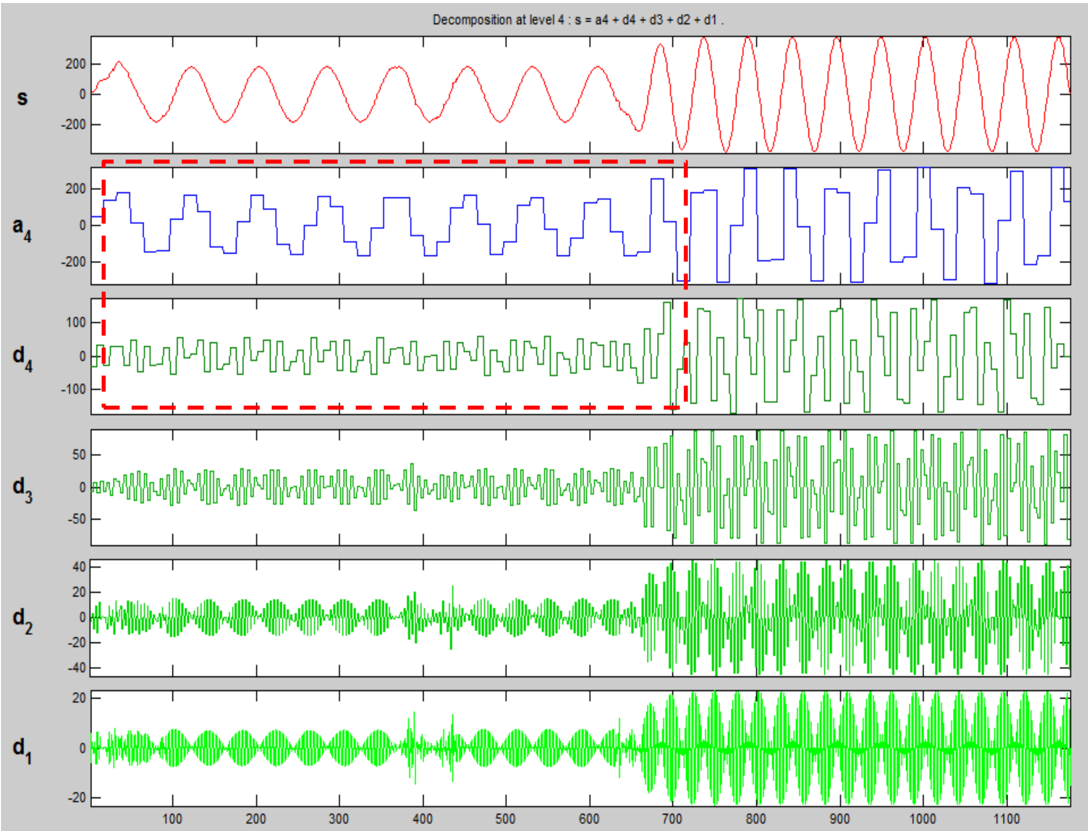

FIGURE 8a: Voltage sag disturbance (sag21.mat) at 4-scale decomposition

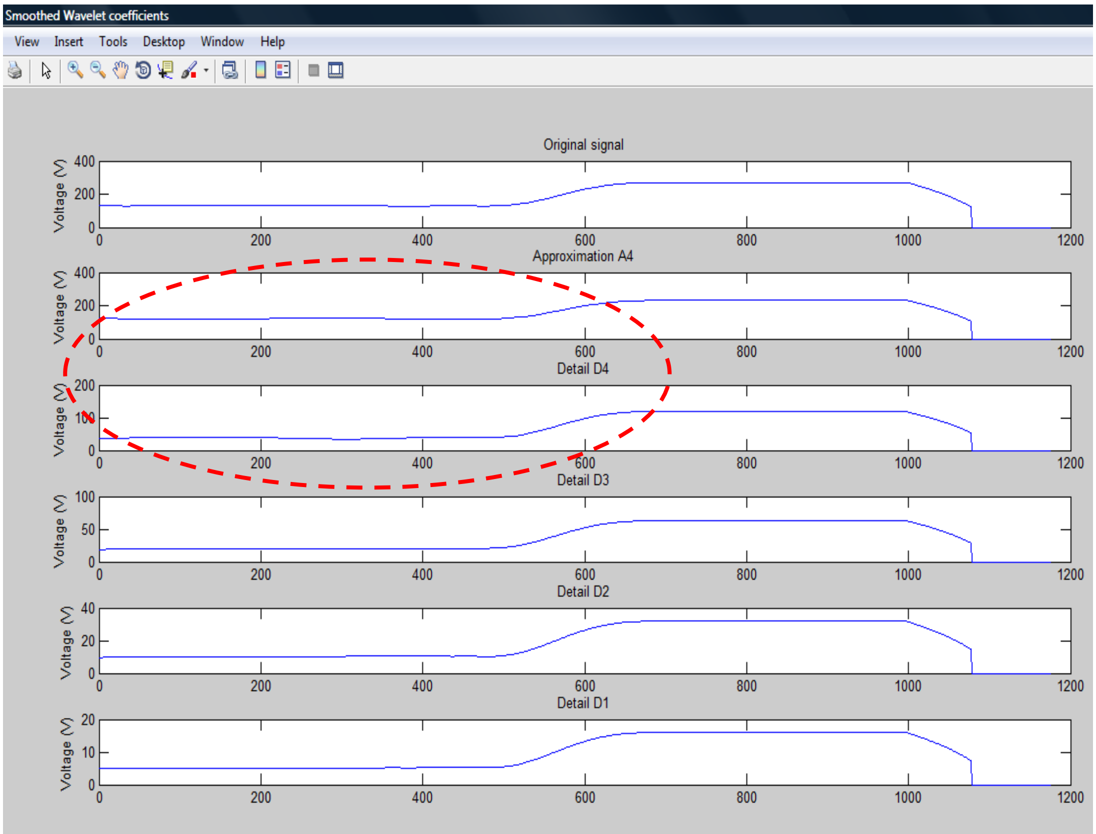

FIGURE 8b: Smoothed wavelet coefficients (sag21.mat)

On the other hand, Figure 9a and Figure 9b demonstrate the sag disturbance (sag19.mat) with time of occurrence is during the end of the voltage signal. The sag disturbance is last for 6 cycles, starting from 11th cycle to the end of the voltage signal. 50.6% of sag disturbance is indicated in Figure 8a where the voltage is dropped from 375V to 185V. The effect of sag disturbance can be visualised in all frequency bands since the sag percentage is reasonably high. However, *a4* and *d4* frequency bands provide the best frequency resolution in order to detect and localise the effect of sag disturbance. Therefore, in order to study the effect of sag disturbance precisely, approximation coefficients *a4* is more favourable, followed by detail coefficients *d4*.

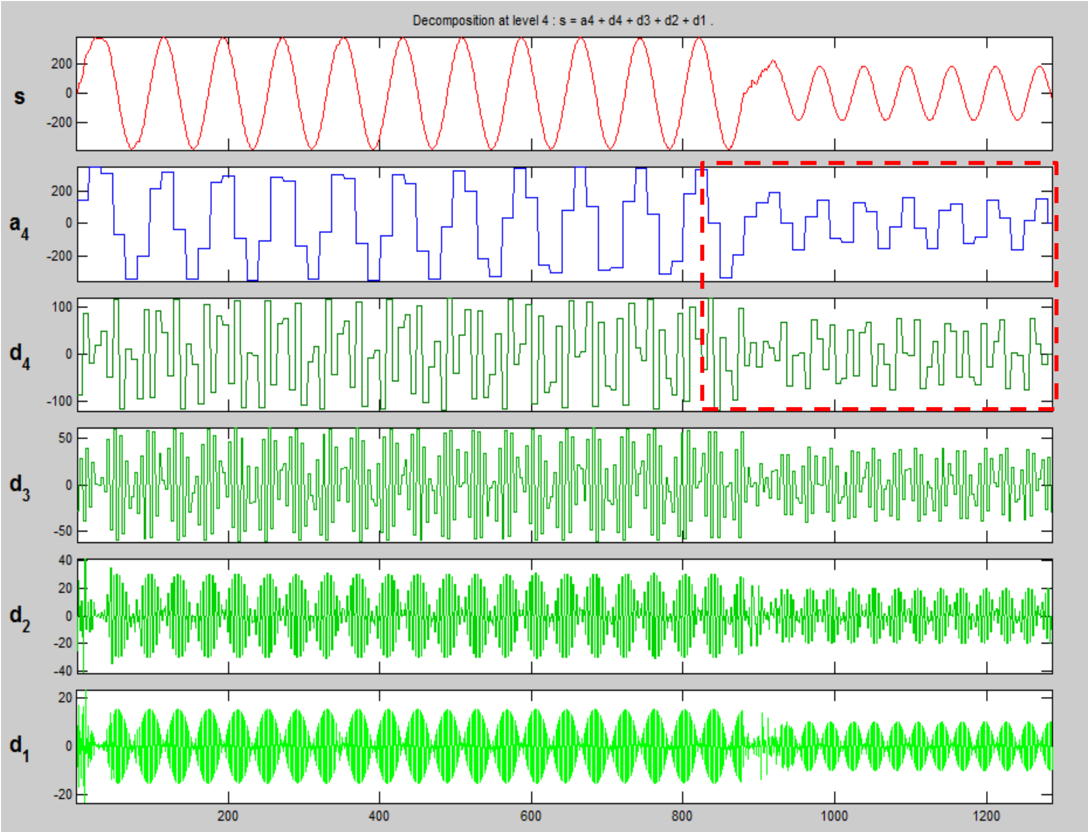

FIGURE 9a: Voltage sag disturbance (sag19.mat) at 4-scale decomposition

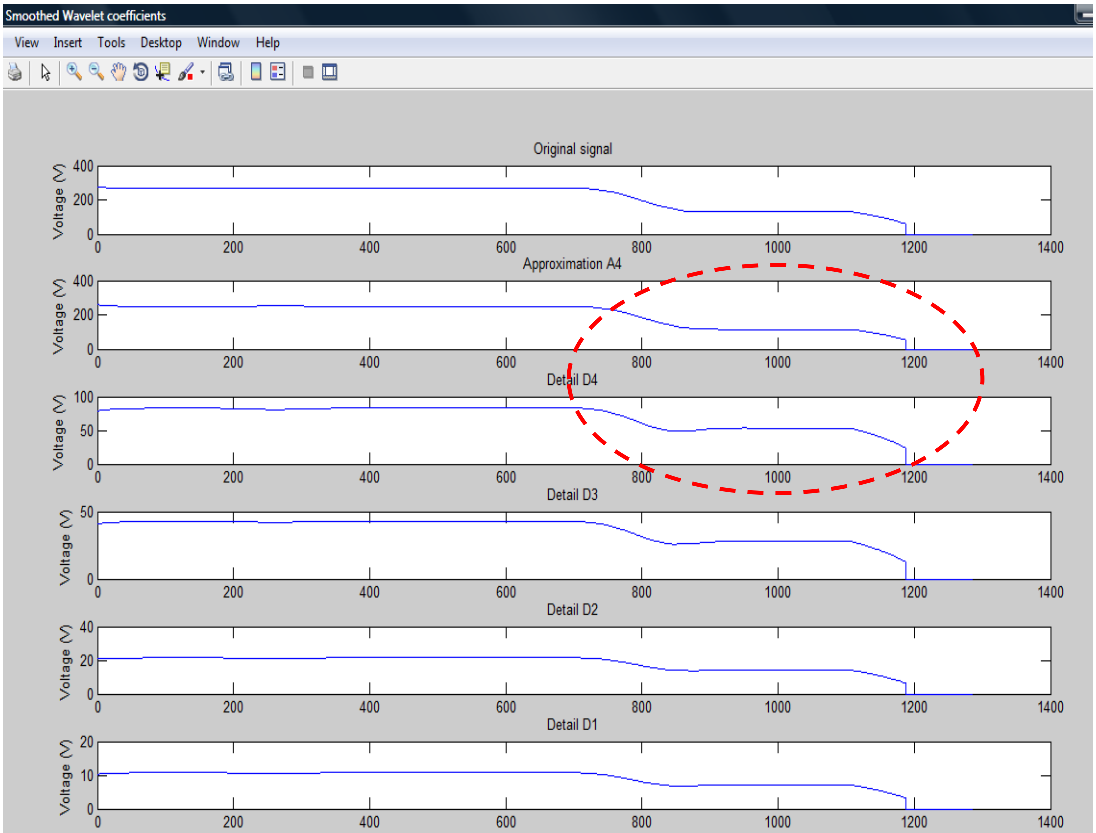

FIGURE 9b: Smoothed wavelet coefficients (sag19.mat)

4.2 VOLTAGE SWELL DISTURBANCE

4.2.1 SEVERE SWELL DISTURBANCE

Due to the sudden load decreased or single line-to-ground faults, voltage swell disturbance is likely to occur. If the swell disturbance is greater than 30%, it is considered as critical swell event. Figure 10a shows a voltage signal with severe swell disturbance with 38.6% of swell variation. During the swell event, the voltage level is deviated from its nominal value where the signal is stepped up from 67.5 V to 110 V. The swell disturbances have resided for 7 cycles, found in 6^{th} to 12^{th} cycles of the voltage signal. Swell disturbance is normally captured in low frequency band such as approximation coefficient *a4* and detail coefficient *d4*. Low frequency band allows sufficient time for the slow variation disturbances such as swell disturbance to transpire before analysis. In addition, the effect of swell disturbance can clearly be described in Figure 10b. By examining Figure 10b, a relatively large expansion which implies the emergence of swell disturbance is noticed particularly in the frequency bands *a4, d4* and *d3*. However, in the high frequency bands such as detail coefficient *d1* and *d2*, the impact of the swell disturbance is hardly to be detected. This is because high frequency bands offer a finer time resolution which is more suitable to detect fast and transient events.

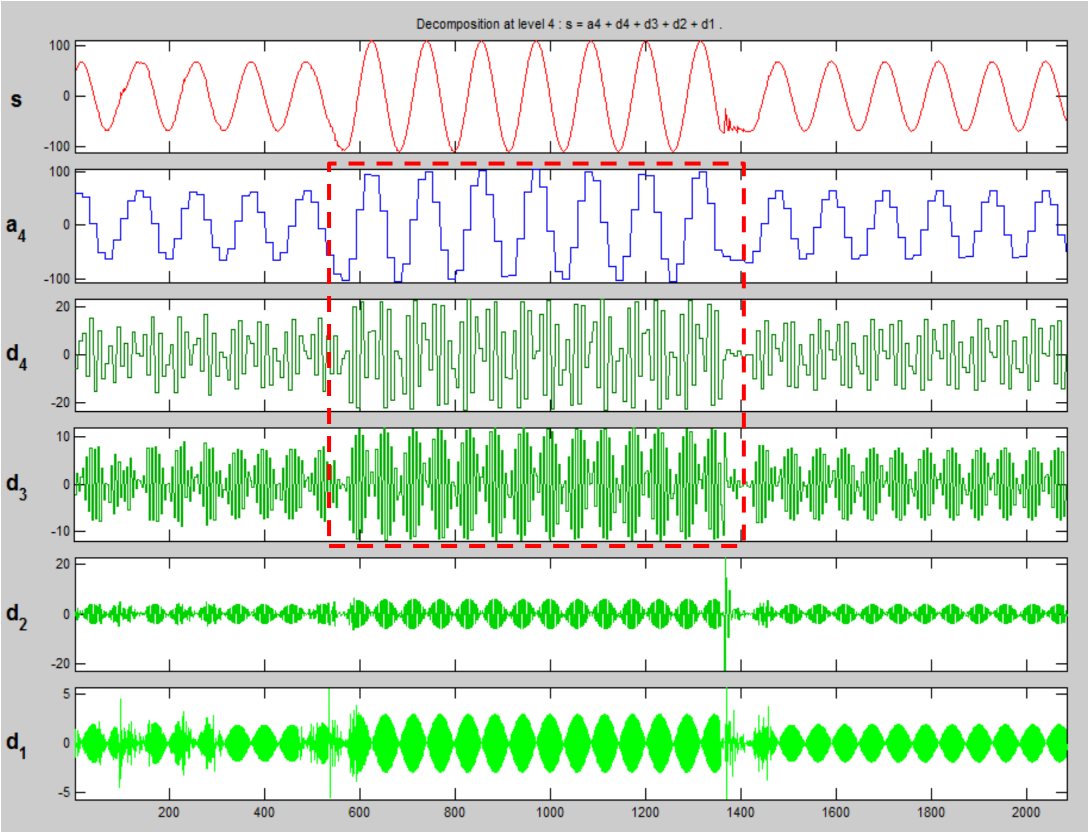

FIGURE 10a: Voltage swell disturbance (swell23.mat) at 4-scale decomposition

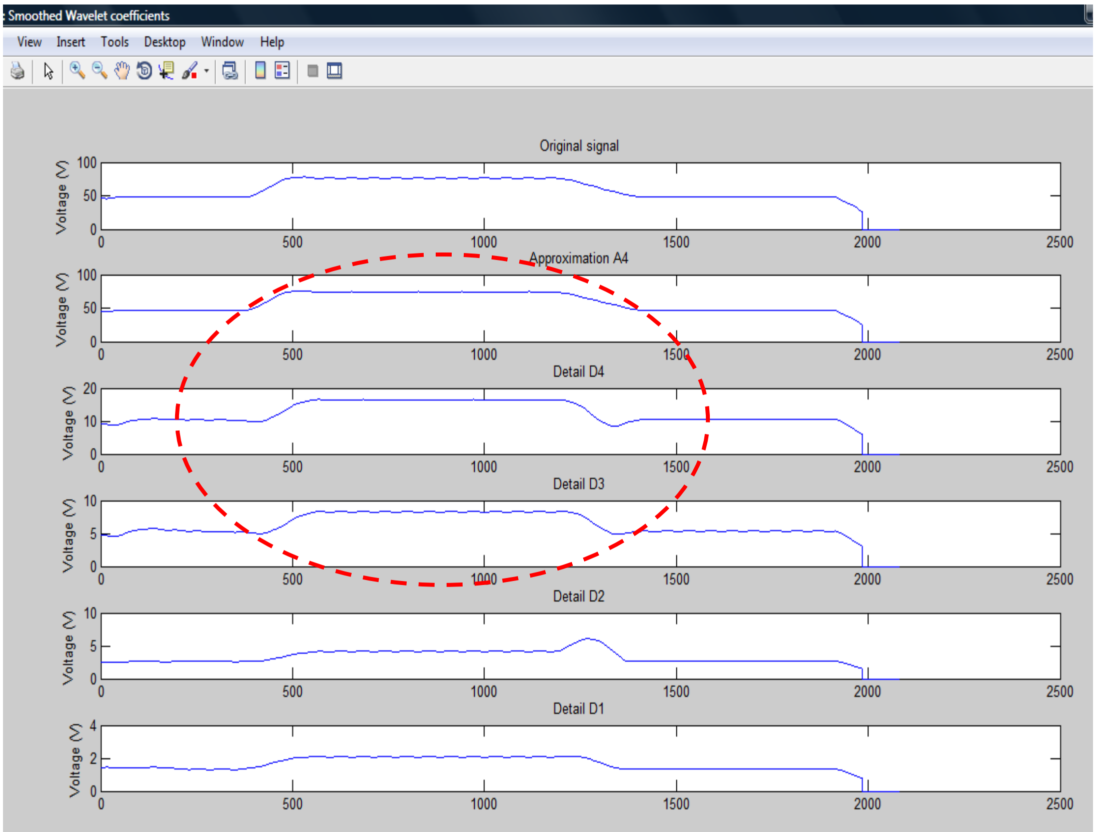

FIGURE 10b: Smoothed wavelet coefficients (swell23.mat)

4.2.2 MINOR SWELL DISTURBANCE

Figure 11a shows a 16.7% swell disturbance for 4 cycles, between 5th and 8th cycle of the voltage signal. The manitude of the signal is increased from 200 V to 240 V during the occurrence of the swell disturbance. Minor swell disturbance is rather insignificant which make it difficult to be distinguished from its background. By using wavelet multi-resolution decomposition method, approximation coefficient *a4* serve as the best frequency band in detecting and analysing swell disturbance. Figure 11b demonstrates the waveform pattern of the wavelet coefficients. A small rise in the amplitude of the signal is spotted especially in the frequency band *a4* and *d4* that describes the effect of the swell disturbance.

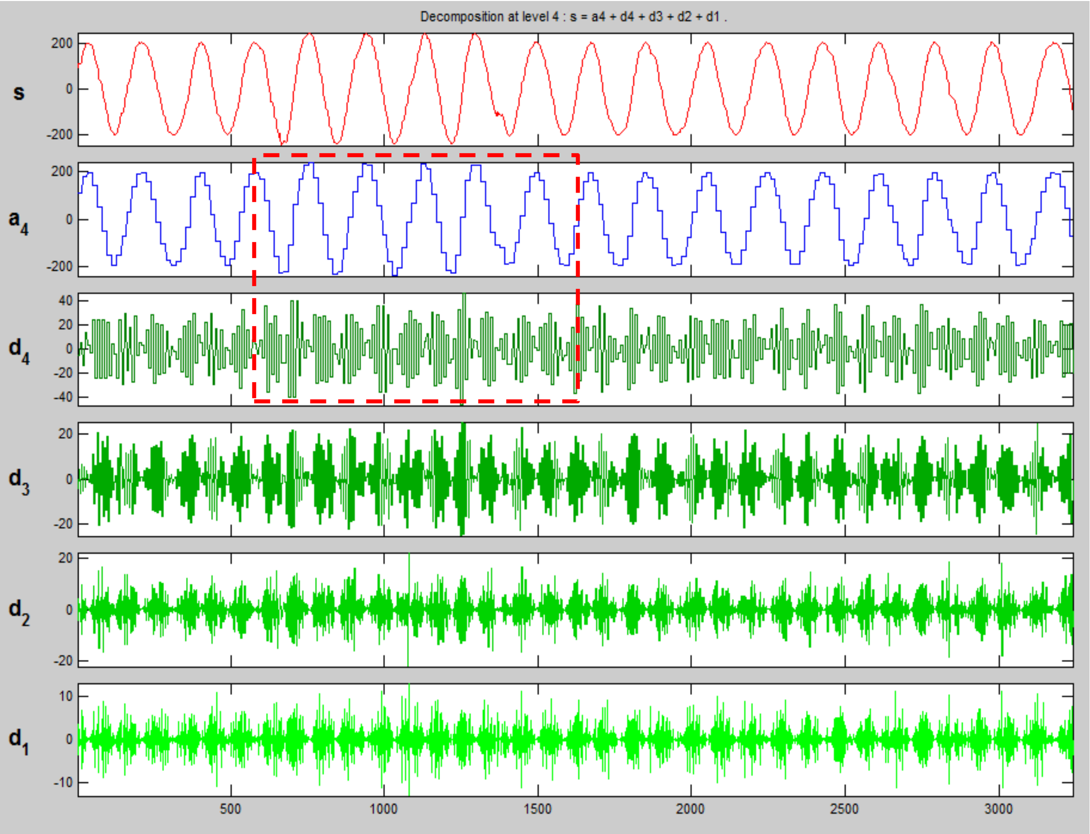

FIGURE 11a: Voltage swell disturbance (swell32.mat) at 4-scale decomposition

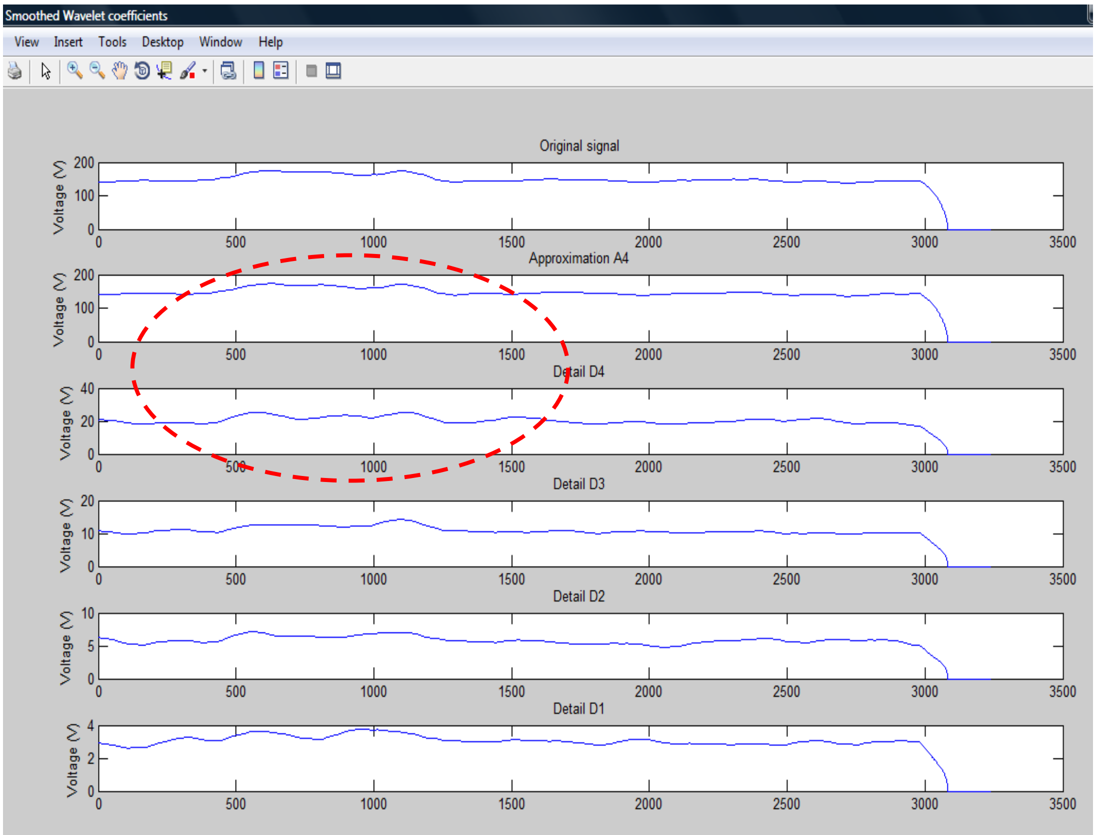

FIGURE 11b: Smoothed wavelet coefficients (swell32.mat)

4.2.3 SWELL DISTURBANCE AT DIFFERENT TIME OF OCCURRENCE

Figure 12a demonstrates the swell disturbance which occurs at the very beginning of the signal. The swell disturbance remains for 5 cycles, starting from the beginning to the 5th cycle of the signal. The voltage signal is generated at 115 V, but due to the swell interrupt, the amplitude of the signal is increased to 182 V. Based on the Figure 12b, the characteristic of the swell disturbance is captured in all frequency bands except detail coefficient *d1*. Frequency band *d1* is the highest frequency among other frequency bands, thus, it failed to capture the slow and long variation swell disturbance. In general, swell disturbance behave like sag disturbance which is best described and presented in lower frequency bands such as approximation *a4* and detail coefficient *d4*.

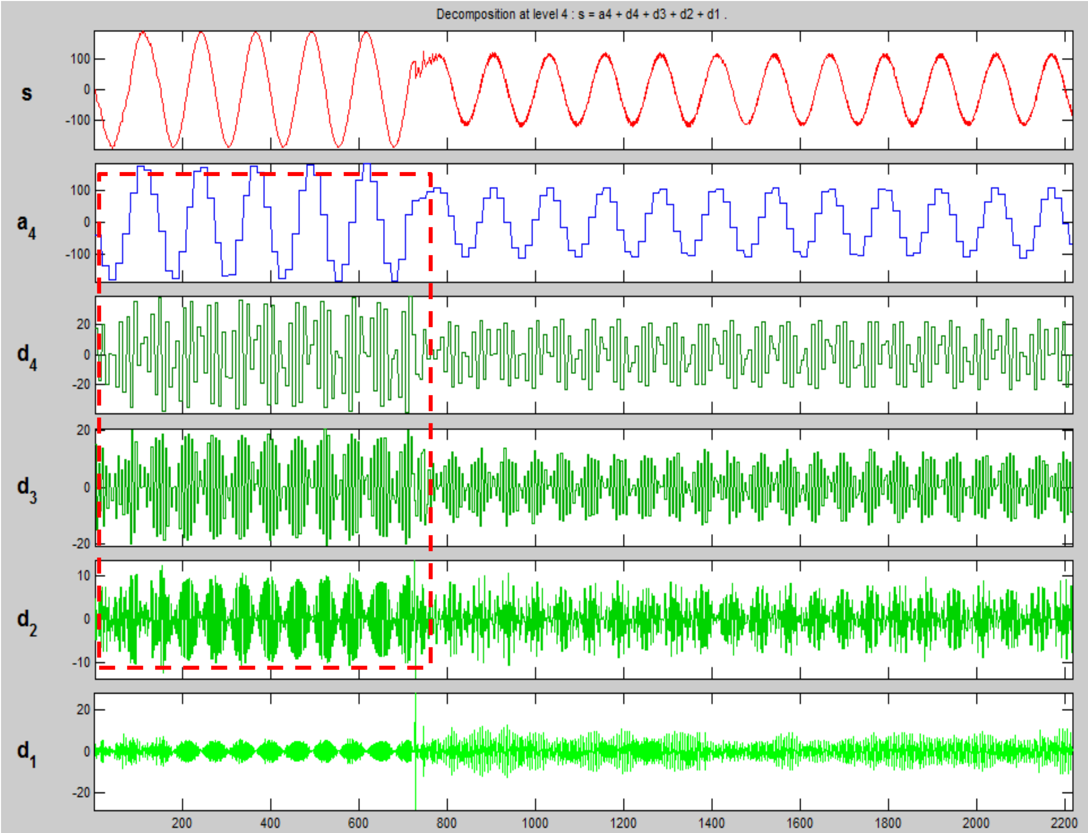

FIGURE 12a: Voltage swell disturbance (swell19.mat) at 4-scale decomposition

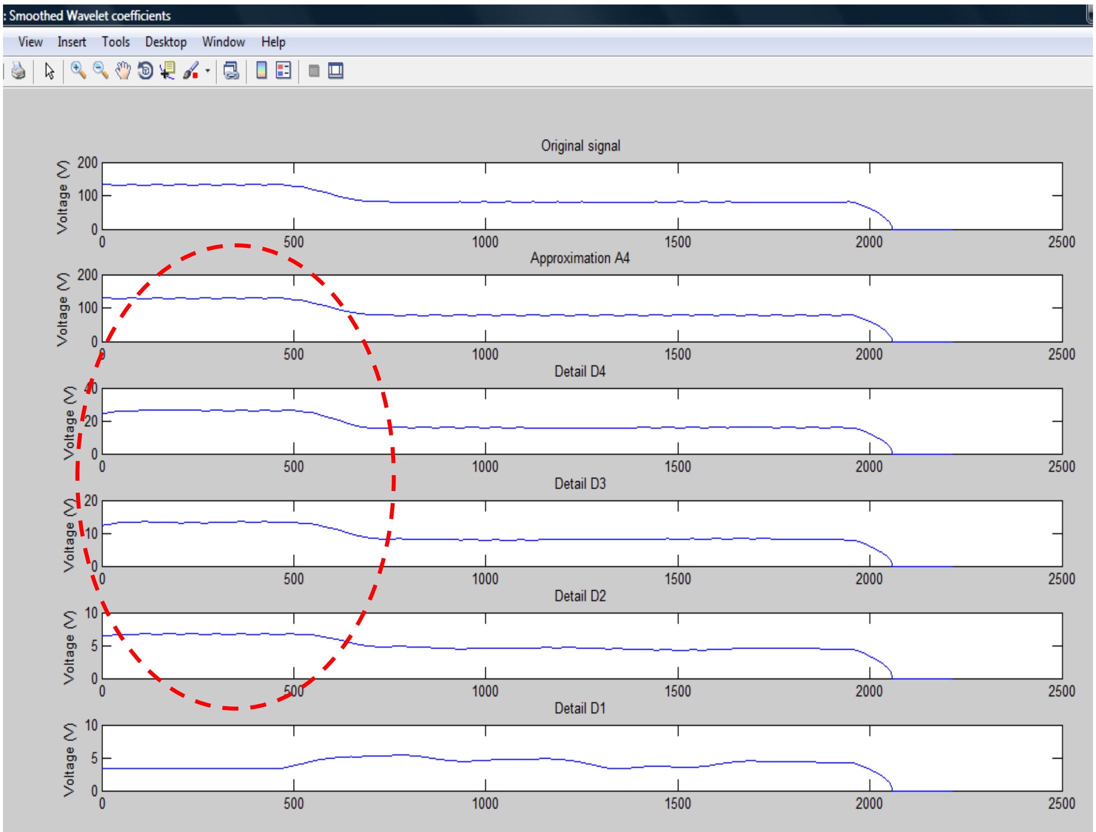

FIGURE 12b: Smoothed wavelet coefficients (swell19.mat)

On the other hand, swell disturbance (swell47.mat) is found during the last few cycles of the signal as shown in Figure 13a. Swell disturbance takes place during the last 3 cycles where the voltage is amplified for 14.4%, from 166 V to 194 V. Based on the Figure 13b, the effect of swell disturbance is clearly identified in all of the frequency bands. However, low frequency bands such as approximation coefficients *a4* and detail coefficients *d4* provides the finest frequency resolution to visualise and distinguish the desirable swell disturbance.

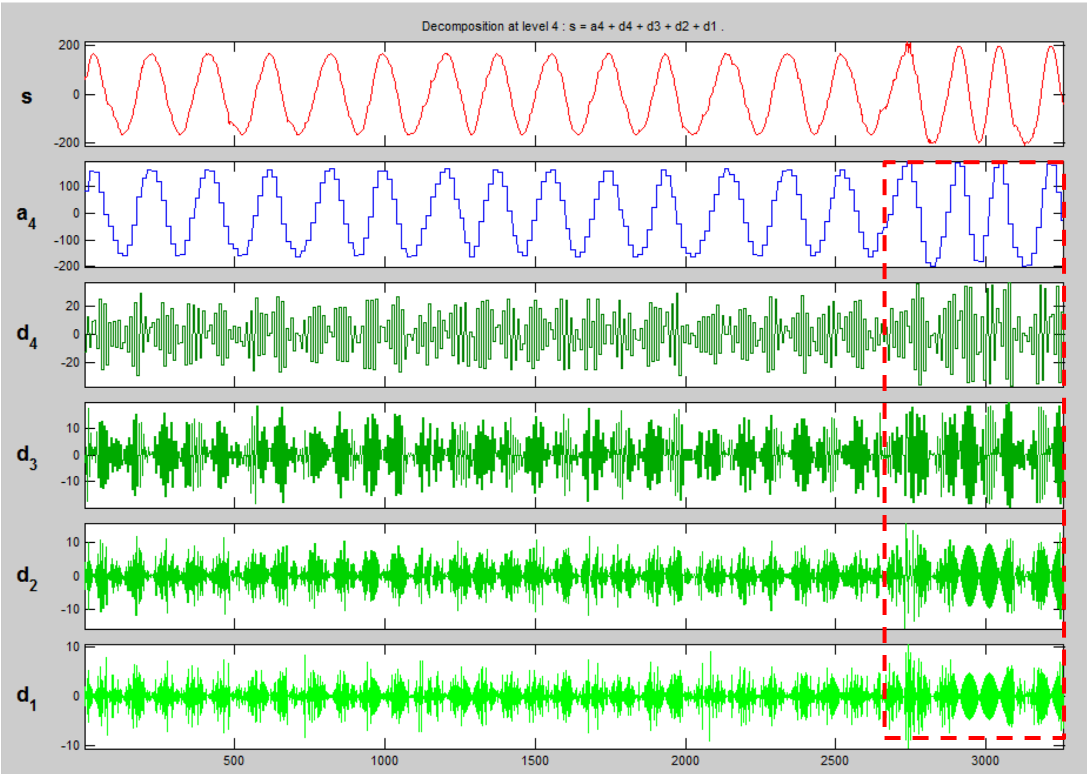

FIGURE 13a: Voltage swell disturbance (swell47.mat) at 4-scale decomposition

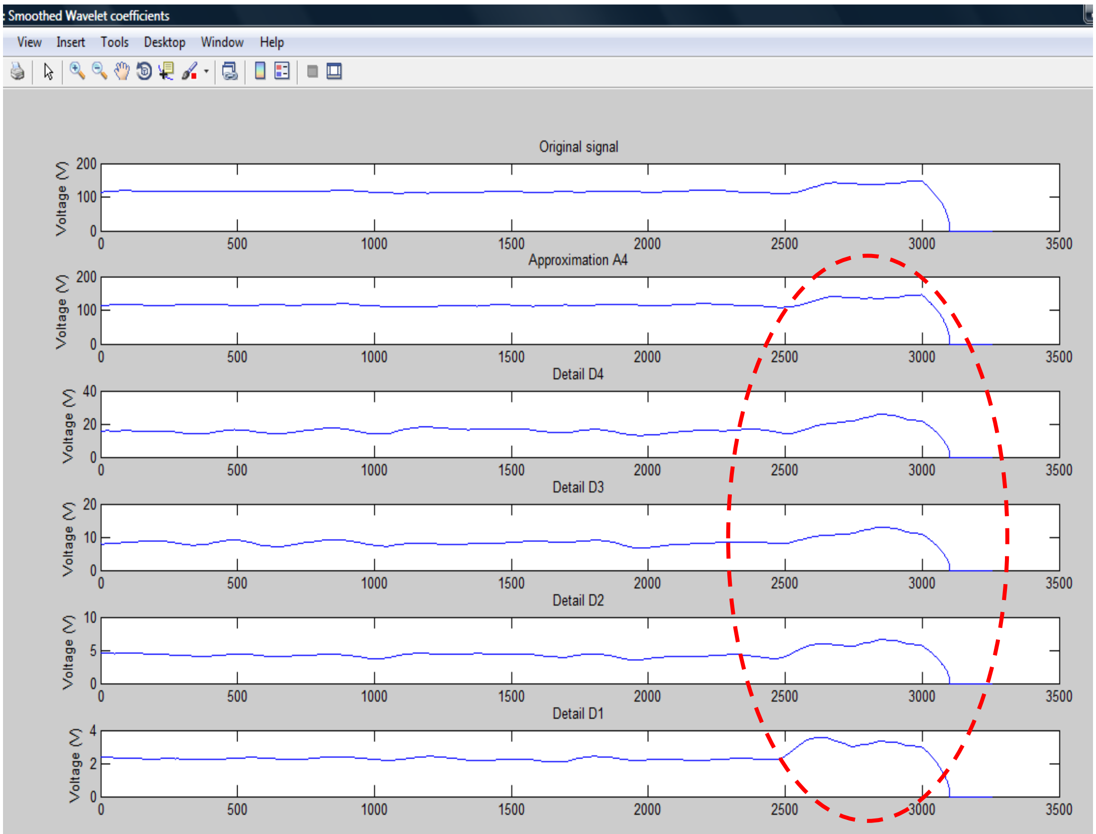

FIGURE 13b: Smoothed wavelet coefficients (swell47.mat)

4.3 VOLTAGE NOTCH DISTURBANCE

Voltage notch is a fast and short transient event that normally occurs during the steady state of the signal. Figure 14a, 14b and 14c show several voltage notch disturbance signals by implementing the proposed technique. In Figure 14a, a small waveform distortion is evidently detected in the highest frequency band *d1*. A spike is observed during the 6^{th} cycle of the voltage signal which indicates the occurrence of voltage notch disturbance. Voltage notch disturbance is normally detected at the higher frequency band, particularly in detail coefficient *d1*. This is because higher frequency bands provide better time resolution in order to capture the fast transient signal such as notch disturbance.

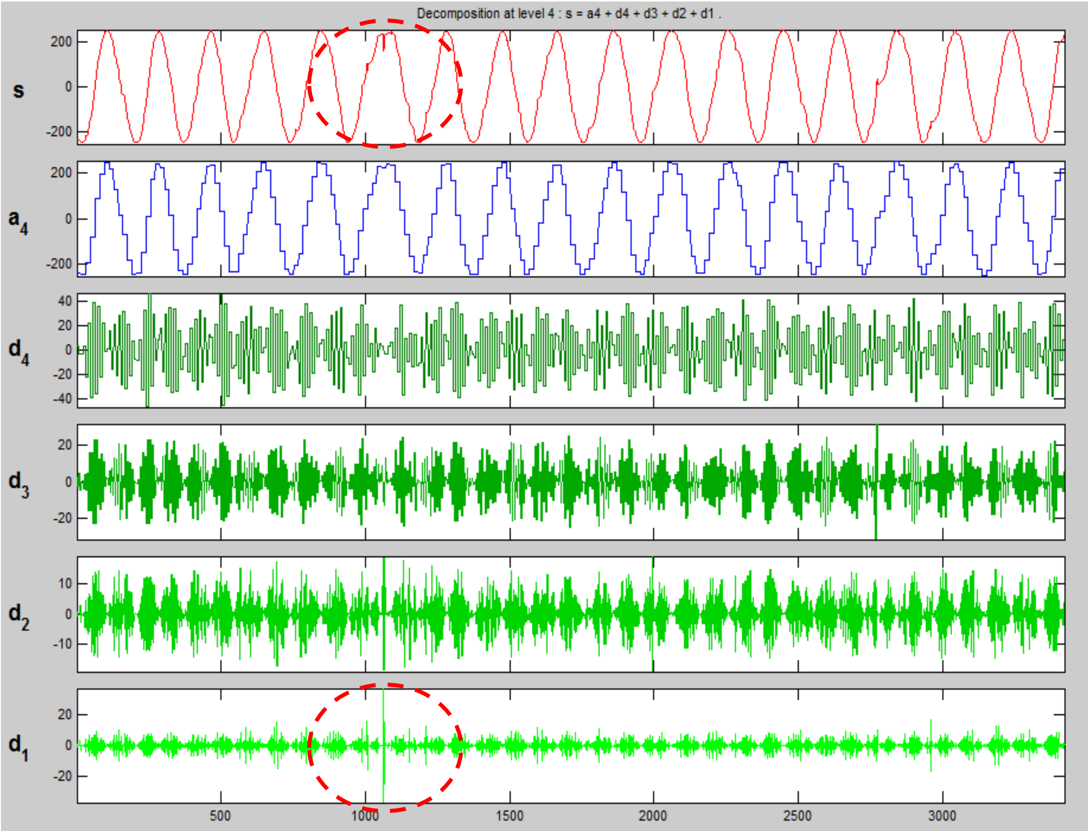

FIGURE 14a: Voltage notch disturbance (notch14.mat) at 4-scale decomposition

On the other hands, Figure 14b presents the significant of the voltage notch disturbance during the steady state of the voltage signal. Several notches have been identified as highlighted by the red circle when the signal is decomposed across different frequency bands. Based on the characteristic of notch disturbance, it is typically detected at the higher frequency band. From Figure 14b, notch disturbances are clearly identified during the 2^{nd}, 6th and 12^{th} cycle of the voltage signal in the detail coefficients *d1* and *d2*. Notch disturbance at the detail coefficients *d1* shows higher deviation from its nominal voltage value as compared to detail coefficients *d2*. Thus, the critical notch disturbance is normally detected at the detail coefficients *d1*. Whereas the secondary notch disturbance is identified at the detail coefficients *d2*.

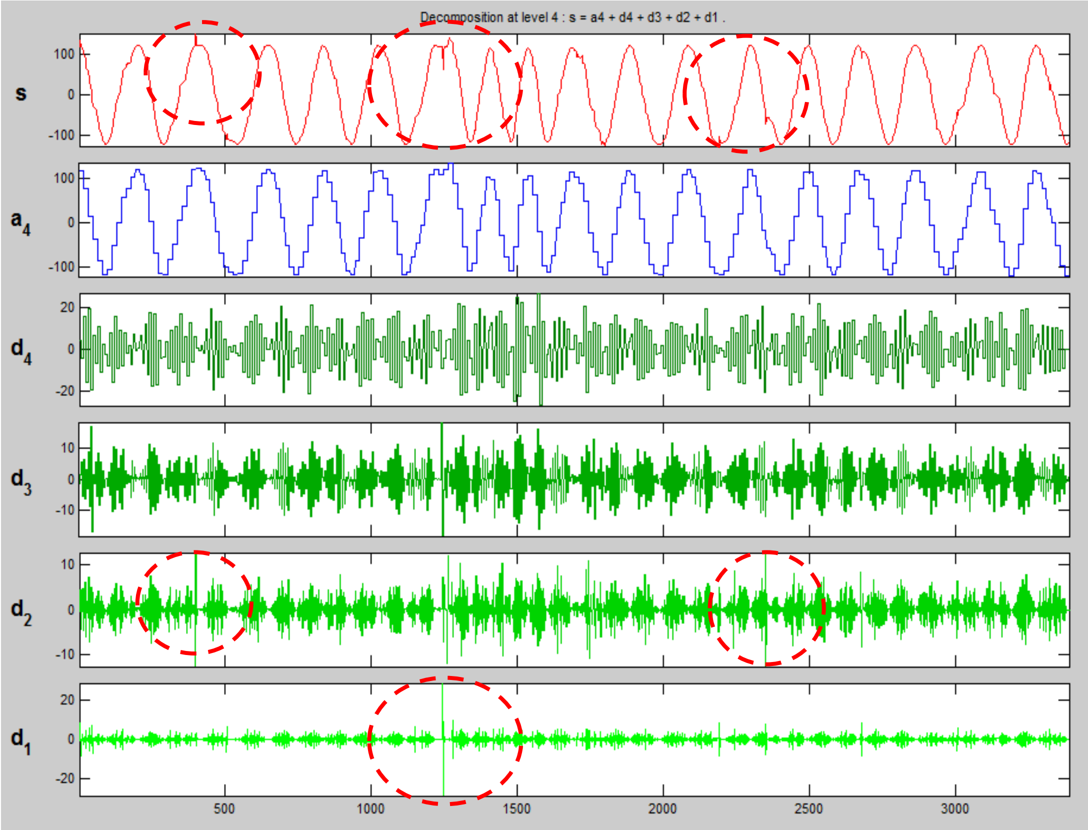

FIGURE 14b: Voltage notch disturbance (notch23.mat) at 4-scale decomposition

In general, notch disturbance is captured at the high frequency band as notch happens for only a very short period of time. Notch disturbance causes the waveform to be distorted from its ideal sinusoidal signal. In Figure 14c, notch disturbance is quite severe and it is detected during the 14th cycle of the signal. As compared to detail coefficient *d2*, *d1* coefficient serves as the best time resolution in recognising and detecting the notch disturbances. This is because detail coefficients *d1* is able to capture the high frequency components of the signal, therefore, fast transient event such as notch disturbance can be easily be noticed and distinguished.

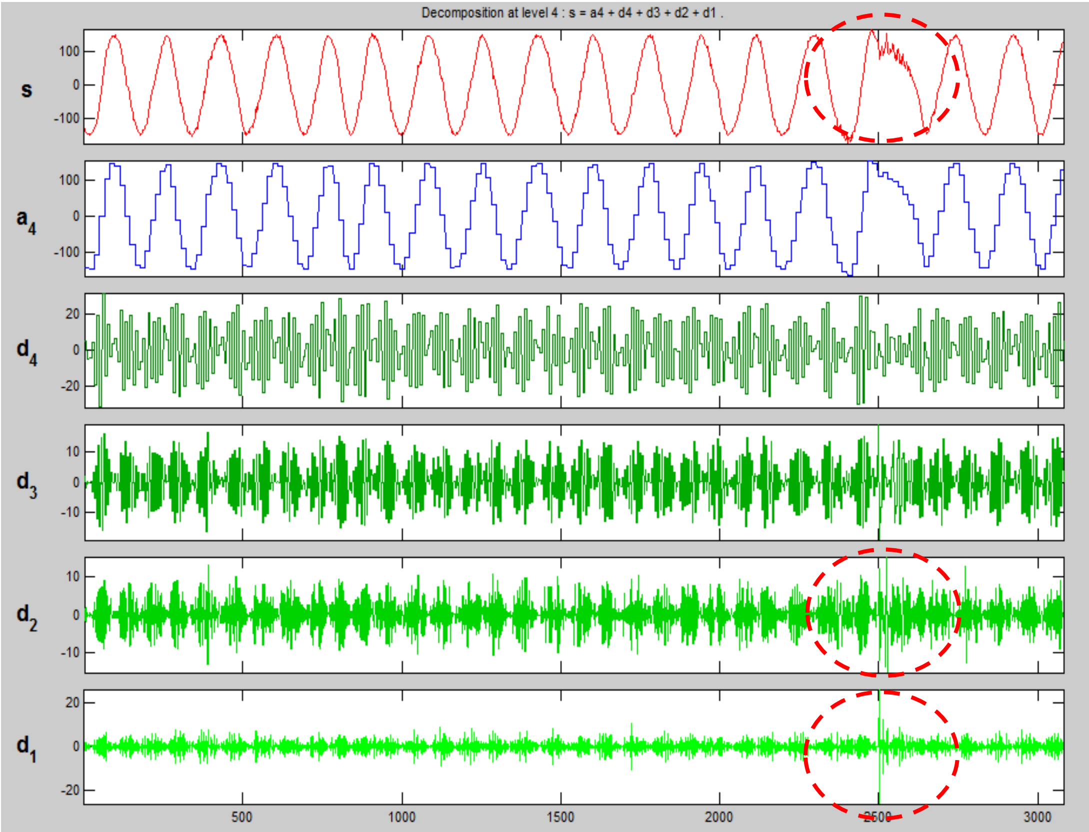

FIGURE 14c: Voltage notch disturbance (notch48.mat) at 4-scale decomposition

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

PQ issues have gain its popularity as the demand for “clean power” is increasing due to the high usage of microelectronic devices. Loss of performance and signal interruptions during the power distribution systems affect the power efficiency and life expectancy. Therefore, the detection and classification of the PQ disturbance is the subject of this paper. In this paper, wavelets multi-resolution decomposition technique is proposed to distinguish 3 types of PQ phenomena: voltage sags, voltage swells and voltage notches. The characteristic of each of the disturbances are discussed and the concept of the wavelet transform is introduced. Decomposition and reconstruction of the voltage signals are conducted in the MATLAB wavelet 1-D toolbox and the decomposition technique used is translated into MATLAB algorithms. Based on the results obtained, voltage sag and voltage swell are detected at the lower frequency bands such as approximation coefficient *a4* and detail coefficients *d4*. Conversely, notch disturbance is captured and identified in high frequency bands such as detail coefficients *d1* and *d2*. Therefore, wavelet multi-resolution decomposition technique with Haar wavelet as the mother wavelets and 4 level of wavelets decomposition is able to detect and distinguish the three types of PQ disturbance signal accordingly.

However, the proposed approach can be further improved by selecting other types of wavelets in the wavelet families instead of Haar wavelets. Daubechies wavelet such as Daub3 and Daub4 are most commonly used in image and signal processing and it may ease in disturbances detection. Besides, the detection and classification of PQ disturbances is more precise and accurate when proper level of wavelet decomposition is employed. Future studies should focus on the relationship between wavelets characteristic and the types of PQ disturbances. A reliable disturbances classification system should be able to precisely identify the types of the PQ events in a short period of time. The PQ disturbances issues shall further be explored and studied to make the classification system automated and user-friendly.

REFERENCES

[1] H. He and J. A. Starzyk, “A Self-Organizing Learning Array System for Power Quality Classification Based on Wavelet Transform,” *IEEE Trans. on Power Del.*, vol. 21, No. 4, Jan. 2006

[2] R. P. Bingham. (1998, Feb.). SAGs and SWELLs. *Dranetz-BMI*. [online]. Available http://www.scribd.com/doc/92681046/Sags-Swells

[3] W. M. Lin, C. H. Wu, C. H. Lin, and F. S. Cheng, “Detection and Classification of Multiple Power-Quality Disturbances With Wavelet Multiclass SVM,” *IEEE Trans. on Power Del.*, vol. 23, No. 4, Oct. 2008

[4] C. Sharmeela, M. R. Mohan, G. Uma and J. Baskaran, (2006) A Novel Detection and Classification Algorithm for Power Quality Disturbances using Wavelets. *American Journal of Applied Sciences.*[Online]. 3 (10), pp. 2049-2053. Available http://web.a.ebscohost.com/

[5] L. W. Cheok, T. K. Saha, and Z. Y Dong. (n.a.). Power Quality Investigation with Wavelet Techniques. *The University of Queensland*. [online]. Available: http://itee.uq.edu.au/~aupec/aupec02/Final-Papers/LW-Cheok1-Z-Y-Dong2.pdf

[6] A. Milchevski, D. Kostadinov, and D. Taskovski , “Classification of Power Quality Disturbances using Wavelets and Support Vector Machine,” *Elecktronika IR Elektrotechnika,*vol. 19, no. 2, Dec. 2013

[7] L. Saribulut, A. Teke, M. B. Latran and M. Tumay (2013, May). Fundamentals and literature review of wavelet transform in power quality issues. *Journal of Electrical and ElectronicsEngineering Research.* [online]. Vol 5 (1), pp. 1-8. Available: http://en.wikipedia.org/wiki/Haar_wavelet#cite_note-22

[8] S.Santoso, E.J. Powers and W.M. Grady, “Electric Power Quality Disturbance Detection Using Wavelet Transform Analysis,” in *Time-Frequency and Time-Scale Analysis, 1994., Proceedings of the IEEE-SP International Symposium on*, 1994, pp. 166-169.

APPENDICES

A. MATLAB Code for wavelet 4-levels decomposition technique (*decomposition.m*)

```
%wavelets multi-resolution decomposition

load sag39.mat

s=sag; %swell,sag or notch depending on signal types


%voltage signal is decomposed at 4-scale with Haar wavelets
[C,L]=wavedec(s,4,'haar');

%extract level 4 approximation coefficients
cA4=appcoef(C,L,'haar',4);
%extract level 1-4 detail coefficients
cD4=detcoef(C,L,4);
cD3=detcoef(C,L,3);
cD2=detcoef(C,L,2);
cD1=detcoef(C,L,1);

%reconstruct original
ori_sig=waverec(C,L,'haar');
%reconstruct level 4 approximation coeff
A4=wrcoef('a',C,L,'haar',4);
%reconstruct level 1-4 detail coefficients
D1=wrcoef('d',C,L,'haar',1);
D2=wrcoef('d',C,L,'haar',2);
D3=wrcoef('d',C,L,'haar',3);
D4=wrcoef('d',C,L,'haar',4);

%determine the size of the signal
[row,column]=size(ori_sig)

%display decomposed wavelet coefficients
figure('name','4-scale Wavelets multi-resolution decomposition');
x=1:row;
subplot(6,1,1); plot(x,ori_sig(x)); title('original
signal');ylabel('Voltage (V)')
subplot(6,1,2); plot(x,A4(x)); title('Approximation
A4') ;ylabel('Voltage (V)')
subplot(6,1,3); plot(x,D4(x)); title('Detail D4');ylabel('Voltage
(V)')
subplot(6,1,4); plot(x,D3(x)); title('Detail D3');ylabel('Voltage
(V)')
subplot(6,1,5); plot(x,D2(x)); title('Detail D2');ylabel('Voltage
(V)')
```

```
subplot(6,1,6); plot(x,D1(x)); title('Detail D1');ylabel('Voltage
(V)')

%Smooth the voltage signal

%initialise the variable
rms_ori=zeros(row,column);
rms_A4=zeros(row,column);
rms_D4=zeros(row,column);
rms_D3=zeros(row,column);
rms_D2=zeros(row,column);
rms_D1=zeros(row,column);

srms_ori=zeros(row,column);
srms_A4=zeros(row,column);
srms_D4=zeros(row,column);
srms_D3=zeros(row,column);
srms_D2=zeros(row,column);
srms_D1=zeros(row,column);

y=zeros(row,column);
y1=zeros(row,column);
y2=zeros(row,column);
y3=zeros(row,column);
y4=zeros(row,column);
y5=zeros(row,column);

xy=zeros(row,column);
xy1=zeros(row,column);
xy2=zeros(row,column);
xy3=zeros(row,column);
xy4=zeros(row,column);
xy5=zeros(row,column);

%smoothing the wavelets coefficients for the 1st time
c=1; a=1;b=160;
d=row-b+1;
for c=1:d
for i=a:b
    y(c)=y(c)+(ori_sig(i).^2);
    y1(c)=y1(c)+(A4(i).^2);
    y2(c)=y2(c)+(D4(i).^2);
    y3(c)=y3(c)+(D3(i).^2);
    y4(c)=y4(c)+(D2(i).^2);
    y5(c)=y5(c)+(D1(i).^2);
end
    rms_ori(c)=sqrt(y(c)/((b-a)+1));
    rms_A4(c)=sqrt(y1(c)/((b-a)+1));
    rms_D4(c)=sqrt(y2(c)/((b-a)+1));
    rms_D3(c)=sqrt(y3(c)/((b-a)+1));
    rms_D2(c)=sqrt(y4(c)/((b-a)+1));
    rms_D1(c)=sqrt(y5(c)/((b-a)+1));

a=a+1;
b=b+1;
end

%smoothing the wavelets coefficients for the 2nd time
[row1,column1]=size(rms_ori)
w=1; a1=1;b1=100;
```

```
v=row1-b1+1;
for w=1:v
for i=a1:b1
    xy(w)=xy(w)+(rms_ori(i).^2);
    xy1(w)=xy1(w)+(rms_A4(i).^2);
    xy2(w)=xy2(w)+(rms_D4(i).^2);
    xy3(w)=xy3(w)+(rms_D3(i).^2);
    xy4(w)=xy4(w)+(rms_D2(i).^2);
    xy5(w)=xy5(w)+(rms_D1(i).^2);
end
    srms_ori(w)=sqrt(xy(w)/((b1-a1)+1));
    srms_A4(w)=sqrt(xy1(w)/((b1-a1)+1));
    srms_D4(w)=sqrt(xy2(w)/((b1-a1)+1));
    srms_D3(w)=sqrt(xy3(w)/((b1-a1)+1));
    srms_D2(w)=sqrt(xy4(w)/((b1-a1)+1));
    srms_D1(w)=sqrt(xy5(w)/((b1-a1)+1));

a1=a1+1;
b1=b1+1;
end

%display the smoothed wavelet coefficients
x=1:row;
figure('name','Smoothed Wavelet coefficients');
subplot(6,1,1); plot(x,srms_ori(x)); title('Original
signal');ylabel('Voltage (V)')
subplot(6,1,2); plot(x,srms_A4(x)); title('Approximation
A4');ylabel('Voltage (V)')
subplot(6,1,3); plot(x,srms_D4(x)); title('Detail
D4');ylabel('Voltage (V)')
subplot(6,1,4); plot(x,srms_D3(x)); title('Detail
D3');ylabel('Voltage (V)')
subplot(6,1,5); plot(x,srms_D2(x)); title('Detail
D2');ylabel('Voltage (V)')
subplot(6,1,6); plot(x,srms_D1(x)); title('Detail
D1');ylabel('Voltage (V)')
```