The Comparison of Threshold Techniques in One-Cycle Sliding Window Length for Transient Event

Saidatul Habsah Asman, Nofri Yenita Dahlan, Ahmad Farid Abidin

Abstract—**Wavelet transform (WT) is an effective method to de-noise the signal based on several attainment de-noising through wavelet threshold methods. In this study, four types threshold technique namely rigrsure, minimaxi, heursure, and sqtwolog as proposed have been tested to de-noise the signal with transient event. This study has been focusing on decomposition coefficient at all levels signals for analysis. The mean square error (MSE) and correlation coefficient (CC) are evaluated to indicate the performance of proposed threshold. The analysis signal is simulated using signal processing tool. From the analysis, rigrsure is the best threshold that can be used for de-noising signals with transient event because it is performed the highest CC and lowest MSE for both one-cycle sliding window and total 21 cycles reconstructed coefficient.**

***Index Terms*— wavelet transform, threshold, de-noise, transient**

I. Introduction

Power Quality (PQ) problems have drawn increasing attention in the operation of power systems due to many reasons, but the ultimate reason is the economic issue [1],[2]. Various disturbances can affect adversely to power quality such as transients, harmonics, voltage sags, voltage swell, voltage notch, and flicker [3]–[7]. Therefore, the automated methods for detection and classification the variety of PQ disturbances are essential as monitoring system so that the equipment can operate effectively [8]. Transient overvoltage is the main focal point in this research work. Transient are severe short-time variations of voltage and current generated by disturbance events such as faults in lines, sudden load changes, switching events, and generation variations. According to the literature, it is known that Wavelet Transforms is widely used as signal processing to analyse the signals [9]. However, noises always present during the data collections. Noises can influence the signals during results evaluation by reducing the performance of test equipment [10].

Eliminating noise from test equipment is one of the key links of PQ detection. Implementing of proper threshold is very crucial to de-noise the signal particularly in wavelet transform [11]. At the present, de-noising technique using threshold based wavelet is more practical than traditional filtering method [12], [13]. The traditional filtering method does not effective in reducing the noise due to the overlapping of noise spectrum and signal spectrum [14]. Valencia *et. al* proposed four threshold techniques to de-noise the unwanted signal in Electroencephalogram (EEG) [11]. Authors used rigrsure, sqtwolog, minimax and heursure threshold technique considered the implementation of various mother wavelet in wavelet analysis. The de-noised methods is evaluated based on mean square error (MSE), peak signal to noise ratio (PSNR), signal to noise ratio (SNR), and cross correlation (XCorr). The best result has been discovered and it belongs to rigrsure.

Wan *et. al* [15] has proposed the selection of mother wavelet, threshold technique and decomposition level in orthogonal test EEG signal. The authors has implemented Daubechies, Symlet and Coiflet as a mother wavelet to compare their similarities. Besides, the sqtwolog, rigrsure, heursure, and minimaxi have been chosen for threshold technique to de-noise the unwanted components. The quality of wavelet threshold are evaluated based on root mean square error (RMSE), signal to noise ratio (SNR) and residual power spectrum (RPS). Authors have used 3, 4 and 5 layers as the decomposition level to test the wavelet. From the results, Coif3, decomposition level 3, Rigrsure have the best performance in the de-noising process. However, both [11] and [15] analysis are based on medical signal information and not practicable for power system signal.

Therefore, this paper proposes comparison study of four types threshold technique namely rigrsure, minimaxi, heursure, and sqtwolog for disturbance signal in power system. The signals contained transient event have been tested to perform which will the best de-noise method. However, the modification has been made on selection of wavelet signals to be de-noised. This study has been focusing on decomposition coefficient at all four levels signals of

This paper is submitted on 13rd March 2017 and accepted on 7th September 2017.This papers explained about identification of maximum loadability in power system using a new technique known as Chaotic Mutation Immune Evolutionary Programming (CMIEP) with line contingencies. This work was supported in part by Universiti Teknologi MARA under the scholarship.

Saidatul Habsah Asman is Master student in Electrical Engineering at Faculty of Electrical Engineering, Universiti Teknologi MARA, 40450 Shah Alam, Selangor. (e-mail: saidatulhabsah93@gmail.com)

Nofri Yenita Dahlan is a senior lecturer (PhD) at Faculty of Electrical Engineering, Universiti Teknologi MARA (UiTM) 40450 Shah Alam, Selangor. (e-mail: nofriyenita012@ppinang.uitm.edu.my).

Ahmad Farid Abidin is an Associate Professor at Faculty of Electrical Engineering, Universiti Teknologi MARA, 40450 Shah Alam, Selangor. (e-mail: ahmad924@salam.uitm..edu.my).

analysis. The mean square error (MSE) and correlation coefficient (CC) are evaluated to indicate the performance of proposed threshold. The analysis signal is simulated in Matlab 2017a.

II. PROPOSED ALGORITHM

The aim of this paper is to evaluate the performance of de-noising technique for transient detection purpose using DWT. Three basic stages represent the de-noising technique are:

i) Decomposition: In this stage, the signal was decomposed into four levels decomposition and mother wavelet type Daubechies (4) had been used.

ii) Reconstructed: In second stage, all the coefficients are reconstructed and the details coefficient are add up to be evaluated.

iii) Threshold: In stage 3, the soft-threshold technique are applied to the reconstructed signal and four types of threshold are implemented to demonstrate their performance towards the signal.

A. Decomposition

The decomposition process in DWT is accomplished by implementing the high pass filter and low-pass filter to the time domain signals. The signals are analyzed at different frequency band using filtering technique to divide the signal into approximation and details coefficient. At first, the original signal is divided into two halves to transfer into the both low-pass and high-pass filter. Then, the output of low-pass filter is further divide into two and delivered to the next filters. The process is continuous until at agreed level which is fourth.

In this stage, the original PQ disturbance waveforms are decomposed using DWT at the desired level j with "Daubechies" wavelet function of order n. The decomposition of PQ waveform into various frequency bands is achieved by applying high-pass filter and low-pass filter to the time domain signals. The flow of division filters is further explained at the next subsection. The signal resolution will measure the accumulation of details information for the next process.

The impulse response h[n] is involved while dispatching the signal across a half band low pass filter. Mathematically, the convolution operation of the signal while filtering processes in discrete time is defined as follow:

$$x[n] * h[n] = \sum_{k=-\infty}^{\infty} x[n].h[n-k] \quad (1)$$

Here h[n] can be any filter's impulse response.

$$y_n[k] = \sum_{-\infty}^{\infty} x[n].h[2n-k] \quad (2)$$

$$y_{high}[k] = \sum_{n} x[n].g[2k-n] \quad (3)$$

$$y_{low}[k] = \sum_{n} x[n].h[2k-n] \quad (4)$$

Where $y_{high}[k]$ and $y_{low}[k]$ are the yields of the high pass and low pass filters after subsampling by 2. Here $y_{high}[k]$ denoted as detailed component and $y_{low}[k]$ denoted as approximate component. The down-sampling of convolution process is illustrated as a figure 1 below.

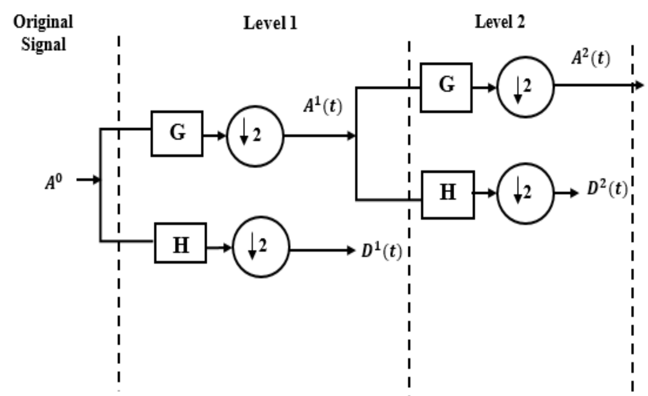

Figure 1: Down-sampling of convolution process in DWT

Figure 2 shows the decomposition coefficient for approximation and details coefficient of finite length signal at level four. Db4 mother wavelet have been chosen for transient detection because it is compact and fast [16]. The high spike in details coefficient signal indicate the transient detection of the signal. The detail coefficient at level 1 (Db1) and level 2 (Db2) shows a clear transient detection with association of noise components.

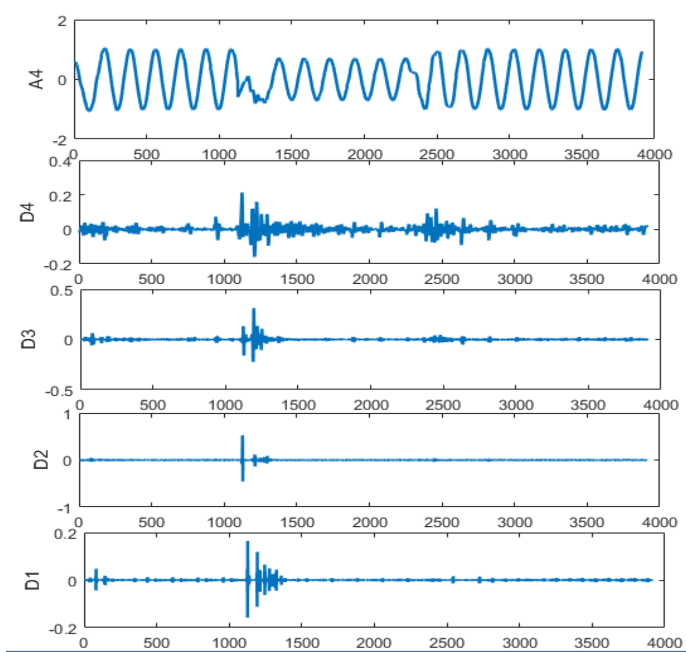

Figure 2: The decomposition of approximation and details coefficient at level four

In this study, one-cycle sliding window technique is implemented for decomposition process due to low computation burden and low border distortion effect [1]. The signal with 3913 samples and 188 samples per cycle has been decomposed in MATLAB 2017a. The total of 21 cycles signals have been decomposed and reconstructed for an analysis purposes.

B. Reconstructed Coefficient

After the decomposition process, the approximation and detail coefficient have been reconstructed as explained in preceding section. In this study, the reconstructed coefficient is defined as:

$$Rec = D1 + D2 + D3 + D4 \qquad (5)$$

Where Rec is reconstruction coefficient, D1 is first level decomposition coefficient, D2 is second level decomposition coefficient, D3 is third level decomposition coefficient, and D4 is fourth level decomposition coefficient.

Figure 3 shows the reconstructed coefficient for details coefficient at all levels. The total of 21 cycles reconstructed coefficient are accumulated as illustrated below. The highest spikes at 0.1seconds indicate the transient event, otherwise many small spikes can be observed through the signal which indicates the noises.

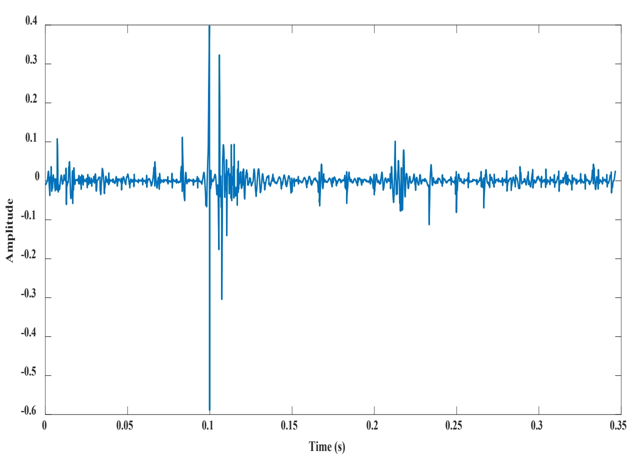

Figure 3: Reconstructed of details coefficient

Figure 4 illustrated the one-cycle signal extracted from reconstructed coefficient which has been de-noised using sqtwolog threshold. Practically, in each one-cycle window length equivalent to 0.0168 second of computation time. Thus, de-noised process is applied after the signal computation of reconstructed operation. The de-noising technique is implemented at each reconstructed coefficient and the process iterated until reach the finite-length of overall one-cycle window signal. The signals tested are accomplished by implementing four types of threshold method and performance of analysis signals are tabulated.

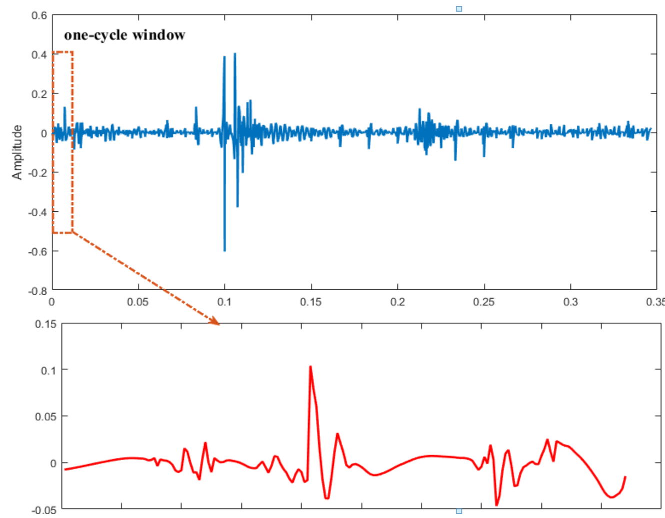

Figure 4: De-noised signal using sqtwolog for one-cycle window

C. Threshold Technique

Four types of threshold techniques are Minimaxi, Sqtwolog, Rigrsure and Heursure have been tested to de-noise the signal. Thresholding selection rules consists in mathematical calculations that can provide a representative noise threshold. All the threshold types will be implemented to evaluate the results and compare their performances. The formulation algorithm of threshold techniques are explained below [17].

i) Minimaxi selection rule uses a fixed threshold to produce a minimaxi performance for the root mean square error against an ideal procedure [11]. Minimaxi equation can be defined as:

$$th_j = \begin{cases} \sigma(0.3936 + 1.0829 \log_2 N, & N > 32 \\ 0, & N < 32 \end{cases} \qquad (6)$$

Where N is the vector length of the signal.

ii) Sqtwolog can be defined as:

$$th_j = \sigma_j \sqrt{2\log(N_j)} \qquad (7)$$

Where σ_j is the mean absolute deviation (MAD) and N_j is the length of the noisy signal. MAD is explicit as:

$$\sigma_j = \frac{MAD_J}{0.6745} = \frac{median_{|\omega|}}{0.6745} \qquad (8)$$

Where ω represent the wavelet coefficient to scale j.

iii) Rigrsure can be defined as:

$$th_j = \sigma_j \sqrt{\omega_a} \qquad (9)$$

Where ω_a represent a^{th} coefficient wavelet square (coefficient at minimal risk) chosen from the vector$W = [\omega_1, \omega_2 \dots \omega_N]$. This vector contain values of the wavelet coefficient squares, from small to large. While, σ is the standard deviation of noisy signal.

iv) Heursure threshold selection rule is a combination of Sqtwolog and Rigrsure methods. Heursure is a dependence method. If the signal to noise ratio is very small, Rigrsure method estimation is poor, whereas the Sqtwolog gives better threshold estimation.

CC: Correlation coefficient represents how similar the de-noised signal with the original signal and was computed using (10).

$$CC = \frac{\sum_{i=1}^{N}\left(x_i - \tilde{x}\right)\left(y_i - \tilde{y}\right)}{\sqrt{\sum_{i=1}^{N}\left(x_i - \tilde{x}\right)^2\left(y_i - \tilde{y}\right)^2}} \qquad (10)$$

Where $\tilde{x}$ is the mean of original signal and $\tilde{y}$ is the mean of de-noised signal.

MSE: It contains square root of the sum of squared errors. The smaller error indicates the signal more faithful to the original signal. The MSE can be defined as:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2 \qquad (11)$$

Where N is the number of sample point, x_i is the original signal, and y_i is the de-noised element.

III. RESULTS AND DISCUSSION

A. *Performance of Threshold*

Figure 5 shows the de-noising result of rigrsure, heursure, minimaxi and sqtwolog for first cycle window of original signal. The rigrsure and minimaxi capable to recover the original signal compared to heursure and sqwolog. It is based on their shape which almost same as original signal contrasting to heursure and sqwolog. To present more accurate results, CC and MSE are implemented as below.

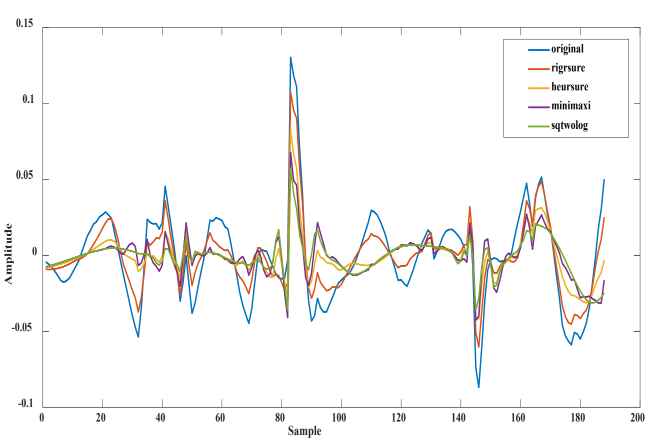

Figure 5: De-noised signal for various threshold types

Figure 6 presented the CC performance of de-noised reconstructed coefficient signal at each one-cycle sliding window. The correlation coefficient is implemented to distinct the effectiveness of threshold technique. From the bar chart below, Rigrsure on soft threshold performing well in comparison with others technique based on their height for most one-cycle sliding window. While, Sqtwolog performing the lowest height indicate the worst result.

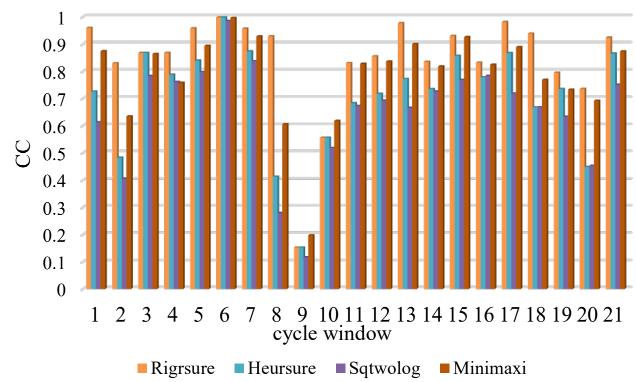

Figure 6: CC values of one-cycle window length

Figure 7 shows the MSE performance of one-cycle window length for the total 21 cycles. The signal implemented with Rigrsure performed the lowest height compared to others. It is indicate that Rigrsure contain the lowest errors in reducing the noises. While, Sqtwolog become the highest errors in reducing the noises based on its height.

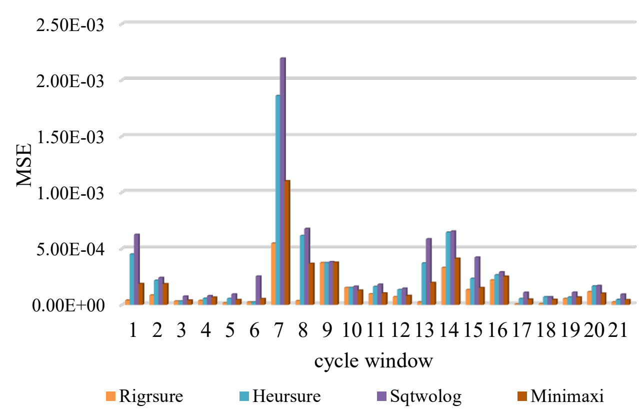

Figure 7: MSE values of one-cycle window length

The tabulated results in Table 1 shows the threshold performance of the total 21 cycle reconstructed coefficient. Rigrsure illustrates the highest CC value which is 0.9366 that indicate the most accurate threshold technique. The rigrsure also shows the lowest MSE value which is 8.4446e-05 hence indicates the highest performances compared to others three. The Sqtwolog resulted the lowest performance of CC and MSE values which are 0.8311 and 3.8698e-04 respectively.

Table 1: Threshold performance of reconstructed details coefficient

Type	CC	MSE
Rigrsure	0.9366	1.5505e-04
Minimaxi	0.8886	2.7355e-04
Sqtwolog	0.8311	3.8698e-04
Heursure	0.8617	3.0707e-04

IV. CONCLUSION

In this paper, the threshold technique such as minimaxi, sqtwolog, rigrsure and heursure are presented to de-noise the unwanted signal components in transient signal. Simulation are performed in Matlab Simulink. Results are evaluated by calculating the correlation coefficient (CC) and MSE value. From the analysis, rigrsure demonstrated the highest CC performance and the lowest MSE results among the others threshold types for one-cycle sliding window technique and at the combination of all 21 cycles respectively. Besides, sqtwolog performed worst performance according to lowest CC and highest MSE value. From the analysis, rigrsure is the best threshold that can be used for de-noising signals with transient event for both one-cycle sliding window and total 21 cycles reconstructed coefficient. In future, the proposed technique can be implemented in various type of power disturbances instead of transient alone to determine the most effective threshold technique.

V. ACKNOWLEDGEMENT

The author acknowledges the financial support given by Ministry of Higher Education (MOHE) Malaysia for sponsoring this research in the form of grant-in-aid 600-RMI/FRGS 5/3 (0103/2016).

3.1.1 REFERENCES

[1] S. H. Asman, A. F. Abidin, and N. Y. Dahlan, 'Extension Mode in Sliding Window Technique to Minimize Border Distortion Effect', vol. 8, no. 1, pp. 237–244, 2017.

[2] I. Molina-moreno and A. Medina, 'Harmonic and Transient State Assessment in the', no. Ropec, 2016.

[3] Z. M. Chen, M. S. Li, T. Y. Ji, and Q. H. Wu, 'Detection and Classification of Power Quality Disturbances in Time Domain Using Probabilistic Neural Network', no. Mm, pp. 1277–1282, 2016.

[4] A. A. Abdelsalam, A. A. Eldesouky, and A. A. Sallam, 'Characterization of power quality disturbances using hybrid technique of linear Kalman filter and fuzzy-expert system', *Electr. Power Syst. Res.*, vol. 83, no. 1, pp. 41–50, 2012.

[5] S. Alshahrani, M. Abbod, B. Alamri, and G. Taylor, 'Evaluation and classification of power quality disturbances based on discrete Wavelet Transform and artificial neural networks', *Proc. Univ. Power Eng. Conf.*, vol. 2015–Novem, 2015.

[6] N. Hamzah, F. H. Anuwar, Z. Zakaria, and N. M. Tahir, 'Classification of transient in power system using support vector machine', in *2009 5th International Colloquium on Signal Processing & Its Applications*, 2009, pp. 418–422.

[7] M. Ijaz, M. Shafiullah, and M. A. Abido, 'Classification of power quality disturbances using Wavelet Transform and Optimized ANN', *18th Int. Conf. Intell. Syst. Appl. to Power Syst.*, no. 1, pp. 1–6, 2015.

[8] L. C. M. De Andrade and M. Oleskovicz, 'Power Quality Disturbances Segmentation Based on Wavelet Decomposition and Adaptive Thresholds', *Harmon. Qual. Power (ICHQP), IEEE 16th Int. Conf.*, pp. 803–807, 2014.

[9] L. C. M. De Andrade, M. Oleskovicz, and R. A. S. Fernandes, 'Adaptive threshold for segmentation of combined Power Quality disturbances', *2015 IEEE Eindhoven PowerTech, PowerTech 2015*, pp. 1–5, 2015.

[10] J. Wang, 'Power Quality Disturbance Signals De-Noising Based on Improved Soft-Threshold Method', no. 2, pp. 1–4, 2007.

[11] D. Valencia, D. Orejuela, J. Salazar, and J. Valencia, 'Comparison analysis between rigrsure, sqtwolog, heursure and minimaxi techniques using hard and soft thresholding methods', *2016 21st Symp. Signal Process. Images Artif. Vision, STSIVA 2016*, pp. 1–5, 2016.

[12] B. Vigneshwaran, R. V. Maheswari, and P. Subburaj, 'An improved threshold estimation technique for partial discharge signal denoising using Wavelet Transform', *2013 Int. Conf. Circuits, Power Comput. Technol.*, pp. 300–305, 2013.

[13] N. Ni, Y. Zhang, L. Jia, and W. Cai, 'A Preprocessing Method based on the Wavelet Threshold De-noising Technique for the Key Variables of Pulverized-coal Concentration', no. 2006, 2010.

[14] S. Hu, Y. Hu, X. Wu, J. Li, Z. Xi, and J. Zhao, 'Research of Signal De-noising Technique Based on Wavelet', *TELKOMNIKA*, vol. 11, no. 9, pp. 5141–5149, 2013.

[15] Y. Wan, F. Chen, and Z. Huo, 'Residual power spectrum analysis in the application of EEG de-noising', *2016 IEEE Int. Conf. Mechatronics Autom. IEEE ICMA 2016*, pp. 2599–2604, 2016.

[16] S. Habsah Asman and A. Farid Abidin, 'Comparative Study of Extension Mode Method in Reducing Border Distortion Effect for Transient Voltage Disturbance', *Indones. J. Electr. Eng. Comput. Sci.*, vol. 6, no. 3, p. 628, 2017.

[17] M. Jayakrishnan, B. N. Rao, K. P. Meena, and R. Arunjothi, 'Optimum threshold estimator for de-noising partial discharge signal using wavelet transform technique', *2015 Int. Conf. Cond. Assess. Tech. Electr. Syst. CATCON 2015 - Proc.*, pp. 76–82, 2016.

Saidatul Habsah Asman received her Bachelor in Electrical Engineering (Power) from Universiti Teknologi MARA (UiTM). She is currently pursuing the M.Sc degree in Electrical Engineering from UiTM since 2016 and at the same time work as Research Assistant at the same faculty. Her research interest includes signal processing, and power quality field.

Nofri Yenita Dahlan received her M.Sc and PhD in Electrical, Electronic Engineering from Manchester University, UK in 2003 and 2011 respectively. She is currently a senior lecturer in Universiti Teknologi MARA, (UiTM). Her research interest includes generation planning, electricity market, energy efficiency and energy saving field.

Ahmad Farid Abidin received his Bachelor in Electrical, Electronic and System from Universiti Kebangsaan Malaysia (UKM), M.Sc degree in Electrical Engineering from Universiti Teknologi MARA (UiTM) in 2005 and PhD in Electrical Engineering from UKM in 2011. He is currently Head at Centre for Electrical Power Engineering Studies (UiTM). His research interest includes signal processing, power quality, protection, and fault analysis. He is the author of 77 articles that has been published.