International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-4, November 2019

Determination of Different Fault Features in Power Distribution System Based on Wavelet Transform

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Abstract: ***Nowadays, there are various signal processing methods that have been studied by many researchers in order to detect faults in power lines. From previous literature, signal processing that works based on time frequency analysis has been proven to accurately detect faults at high speed. In this study, wavelet transform is adopted to analyse fault occurrences on power line of distribution network. Three types of faults due to lightning, switching and short circuit fault were analysed based on their voltage waveform profiles. 'Daubechies' 4 (db4) mother wavelet and four levels decomposition were implemented to extract the features. Approximation at level 4 (A4) and detail coefficient at level 1 to 4 (D1-D4) were extracted to evaluate the energy, skewness, and kurtosis. Based on the results, lightning showed the highest energy, skewness and kurtosis compared to the short circuit and switching voltage waveform. Therefore, these features can be utilized as the new parameters for fault detection in a power system network***

Keywords: fault, features extraction, lightning, wavelet transform, distribution network.

I. INTRODUCTION

Electrical utility has an important role in contributing to the economic growth and development of a country by improving the reliability and quality of electric power supply. Based on the research findings, power distribution networks are exposed to fault occurrence due to their position over a huge graphical area [1]. Fault classification is important for post-fault analysis and power restoration.

Manuscript published on November 30, 2019.
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Fast and accurate classification will help to reduce the outage in power supply in preventing further proliferation of economic losses. Correct fault classifications enable fault diagnosis system to gain the estimation of the fault location [2]. In recent years, there have been numerous research studies conducted on the classification of short circuit fault events. The short circuit fault types can be divided into symmetrical
and unsymmetrical faults. Single line to ground An effective short circuit fault classification scheme is necessary for operators to deal with the increasing amount of power carried by the distribution network. fault and three phase fault are recorded as the most frequently occurred faults in the network. These faults have been extensively classified based on the classifier employed [3]. The focus of this paper is on transient overvoltage fault as it can eventually lead to be a permanent fault. Transient overvoltage fault can be due to lightning strike on the power line or switching heavy load on the system. All these faults should be classified immediately to prevent more losses and further protection action must be considered. Various studies have been conducted to classify the fault types in the electrical system decoded using signal processing method. In [4], Hun-Chul et. al proposed fault clearance detection using wavelet transform based on neutral current waveform. However, the study focused on evaluation of the detail 2 coefficient to detect only the switching effect in distribution power line. In [5], classification of lightning and faults using wavelet transform based on the current signal was proposed. The evaluated result was further analysed using travelling wave theory to identify fault location. Apart of analysing the waveform, wavelet transform can also be adopted to extract the energy value from the coefficient. In [6], Mamta et al. proposed wavelet transform to extract energy at the third data window. However, the author only analysed short circuit fault and did not do the features extraction in their study to reduce the computational burden. In contrary, Sauvik et al. proposed the detection of fault when the transmission line is installed with thyristor controlled series (TCSC) [7]. This technique evaluated the energy spectrum using detail 1 wavelet coefficient (D1). The research gap among previous research is to consider the above mentioned case under lightning causes. Previously, many studies have used signal processing method on various fault types. However, it is still unclear on how much the transient faults such as lightning and switching can affect the performance of power supply to consumers.

Thus, it is significant to perform the analysis of transient fault sources behaviour through signal processing features. In this paper, a fast detection of fault due to lightning, switching, and short circuit fault using wavelet transform focusing on discrete wavelet transform (DWT) is proposed. Features from three phase voltages are extracted using wavelet transform. Db4 mother wavelet is chosen and further analysed using extracted energy.

Finally, the statistical feature types of skewness and kurtosis are extracted from the detail coefficient. The extraction of energy features, skewness and kurtosis are the main contribution of the proposed work. Performance of the proposed method was tested on 11 kV 15-node distribution feeders simulated through MATLAB Simulink software.

II. METHODOLOGY

Basic Structure of Fault Detection in Distribution Line

This paper proposes two main parts for analysis process. First part is modelling the distribution system by using MATLAB Simulink for signal generation. Second part consists of signal analysis using signal processing method. The flowchart of the proposed technique is as shown in Fig. 1. In this flowchart, different types of faults (lightning, short circuit, and switching) are applied at different parts of network. Next, the signals are processed using wavelet followed by the extraction of the features. The prediction process is based on these features. Three cases of faults were generated from 15-node test feeder as shown in Fig. 2 based on reference [8]. Table 1 summarizes the parameters used in the employed test feeder. Direct lightning impulse was generated using Marx generator model as in Fig. 3. The impulse voltages and their appliances to a test object were defined based on national and international standards in order to simulate the effect of transient overvoltage. Time parameters of lightning impulse voltage are shown in Fig. 4 according to IEC standard [9]. The time parameters were set at 1.2µs for front time (1.5*(t_{90}-t_{30})) and 50µs (t_{50}-t_0) for time to half value. Marx generator parameters were set such in Table 2 based on [10] which consisted of switch, two capacitors and two resistors. For switching capacitor, a 100 kVar of capacitive reactive power was paralleled to the 11kV power lines. At bus 11, voltage waveform was recorded and was analysed using DWT. While the short circuit fault was generated by implementing three phase fault block into Simulink. Fault resistance of 25 ohms and ground resistance of 0.01 ohm were set to generate single-line-to ground fault (SLGF) at phase A. The signal of voltage waveform was evaluated and analysed at phase A only for all cases.

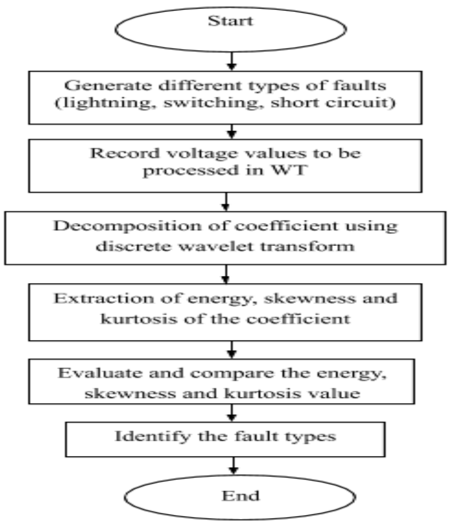


Fig. 1 Flowchart of the developed fault type detection technique

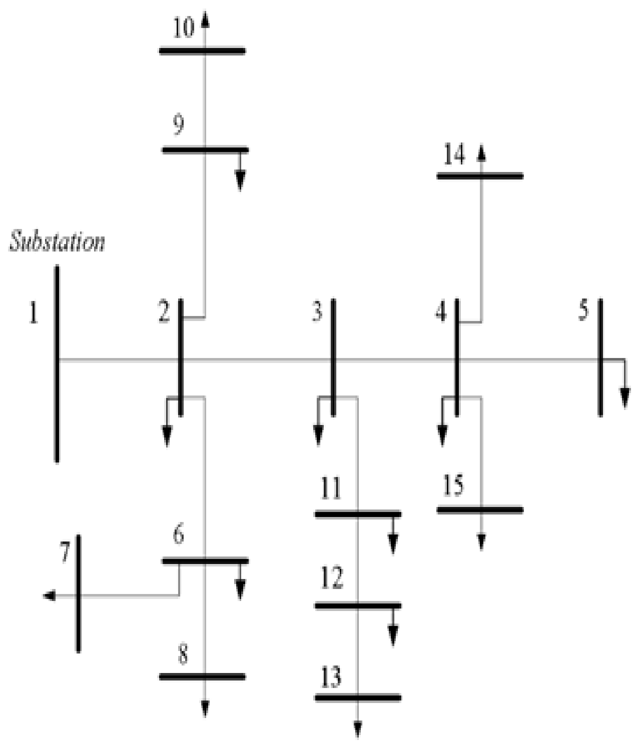


Fig. 2 Single-line diagram of 15-node radial distribution feeder

Table. 1 Parameters of the system

Parameters	Value
Source feeder	11kV, 3MVA, 50Hz
DG source	11kV, 0.6MVA, 300kW
Bus	15 bus

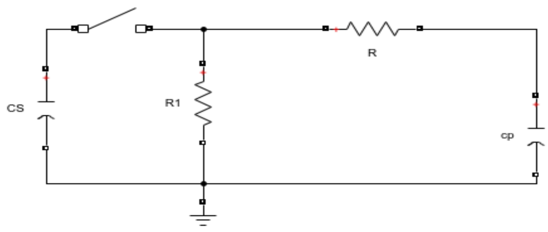


Fig. 3 Schematic diagram of Marx generator model

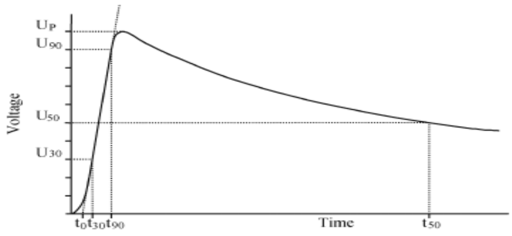


Fig. 4 Heidler function

Table. 2 Parameters of the Marx generator model

Component	Parameter value
Cs	20000e-12 F
Cp	1000e-12 F
R	420.44 Ohm
R1	3.42e3 Ohm

Discrete Wavelet Transform Theory

The application of DWT in power system analysis becomes a popular tool nowadays due to its capability to analyse non-stationary power spectrum [5,11–16]. WT developed by Morlet has been widely used in numerous studies such as in medical, electrical and geophysics. WT can extract time and frequency information simultaneously from an original signal. Mother wavelet function used in WT operates as a basis function to analyse non stationary signal effectively. Mother wavelet function, $\psi\,(t)$ equation is defined as:

$$\psi\,(t)_{(a,b)} = \frac{1}{\sqrt{a}}\psi\left[\frac{t-b}{a}\right] \quad (1)$$

ψ is the mother wavelet while 1/a represents frequency and $1/\sqrt{a}$ is the normalizing constant of each scale parameter. The parallel translation of time axis, t is represented as b. Terms a represents the dilation which determines the frequency length of the wavelet, while b is the translation which determine the shifting position. Daubechies 4 (Db4) mother wavelet was adopted to detect the fault signal. The ability of the scaling functions to reproduce polynomials or known as vanishing moment property is a good part of the successful Db4 wavelet [1]. Time detection information and detail frequency acquisition were based on these parameters.

In this paper the signal was analysed at different frequency bands with different resolutions using the digital filtering techniques through DWT. This was significant in dividing the signal into approximation and detail signals [6,17–20]. The signal has to comply with high pass and low pass filters. At the first stage, the original signal was slashed into two halves of bandwidth and before being shipped to both of the filters. Later, the output from low pass filter was divided into half of frequency bandwidth, and further shipped for the next stage. These steps were iterated until they met at an agreed level which was at the fourth level. These iteration steps are known as iterated filter bank. The accumulation of detail information was measured by resolution of the signal, which was altered by filtering operations and the scale was rectified by the down sampling and up sampling operations.

The relation between low pass and high pass filters with the mother wavelet or known as scalar function, ψ(t) and the wavelet function, ϕ(t) respectively can be defined as follow:

$$\phi(t)=\sum_k g[k]\phi[2t-k] \quad (2)$$

$$\psi(t)=\sum_k h[k]\phi[2t-k] \quad (3)$$

The relation between low pass filter and high pass filter is not independent to each other. They are related by:

$$h[L-1-n] = (-1)^n g[n] \quad (4)$$

Where $g[n]$the low is pass filter, $h[n]$is the high pass filter, L is the filter length (total number of points). Fig. 5 illustrates the block diagram of wavelet decomposition signal. D1, D2, and D3 are the output of detail decomposition that have been decomposed from high pass filter and low pass filter respectively.

The analysed signal then will utilize D1 for extraction process. From the details coefficient, energy value was extracted and evaluated for each of the cases. The equation for energy wavelet is:

$$En=\sum |(cD)_{(N)} \quad (5)$$

Where En represent energy wavelet, and $cD_{(N)}$ represent details coefficient at level N.

The skewness and kurtosis of each level were also evaluated using equation (6) and (7) respectively:

$$SKD_i = \frac{E(D_{ij}-\mu_i)^3}{\sigma_i^3} \quad (6)$$

Where μ indicates the mean of D_{ij}, σ the standard deviation of D_{ij} and $E(t)$ stands for the expected value of the quantity.

$$KTD_i = \frac{E(D_{ij}-\mu_i)^4}{\sigma_i^4} \quad (7)$$

Where μ indicate the mean of D_{ij}, σ is the standard deviation of D_{ij} and $E(t)$ stands for the expected value of the quantity.

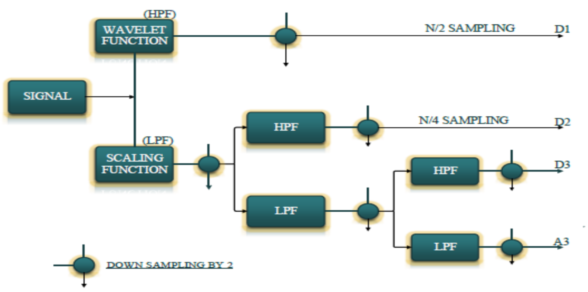


Fig. 5 Sub band filter of signal into low pass and high pass filter [21]

III. RESULTS AND DISCUSSIONS

Results

This paper presents the findings of voltage features analysed in WT as the parameter for identification of fault types. The specified variable parameters condition and the algorithm were simulated in the MATLAB 2018a Simulink and command window respectively.

Approximation and Detail Coefficient Results

The signal was analysed using data generated from bus system at 8.906 kHz sampling rate. This approach produced 512 samples per cycle at 0.02s and the fault was set to occur at 0.1s. As a result, 17 cycles window were generated at 0.35s runtime. However, only one cycle window signal containing fault inception was extracted in matrix array for decomposition process. Fig. 6 shows normal signal waveform generated and one cycle window length signal (red box) was used for an analysis.

During the analysis, signal was decomposed into approximation and the details coefficient is as shown in Fig. 7. Any fault occurrences detected in wavelet should produce spikes at each coefficient level. However, each spike in details consists of different magnitude. The various spikes magnitude influenced by different fault causes are as shown in Fig. 8.

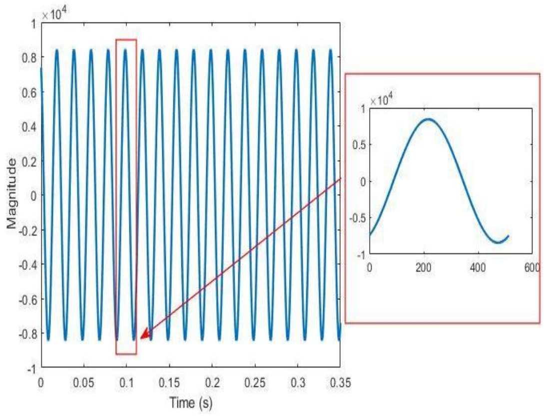


Fig. 6 One cycle window signal extracted for an analysis

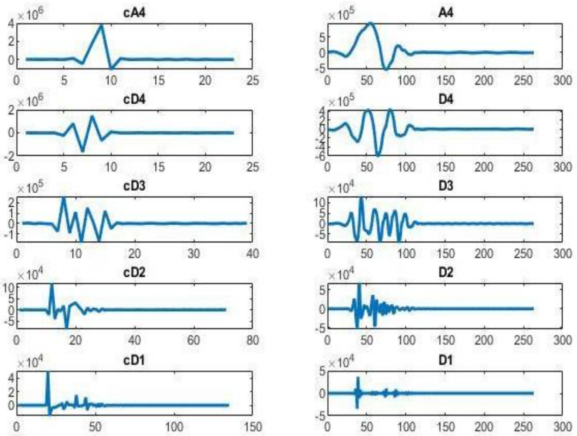
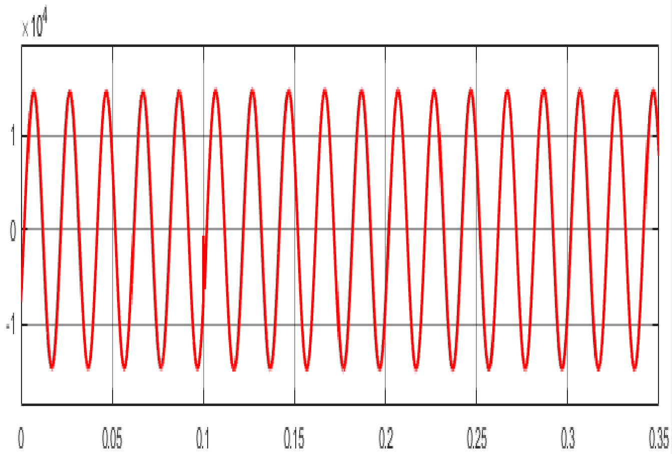
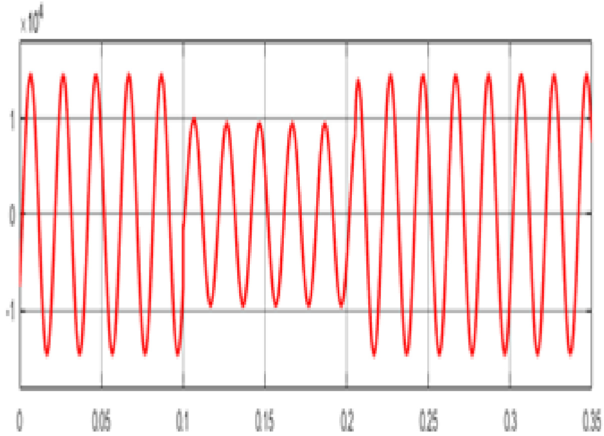


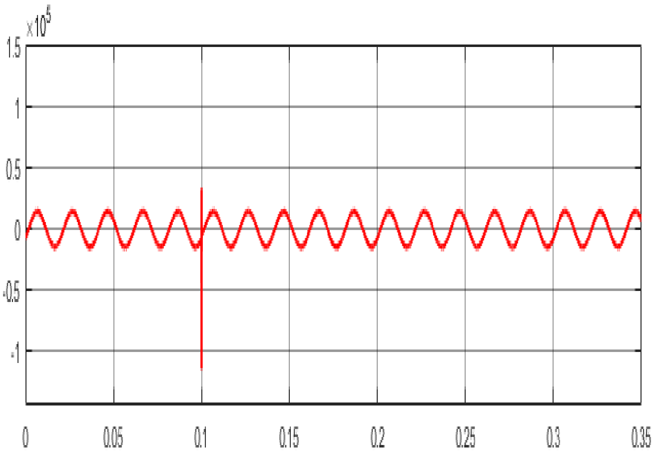
Fig. 7 Approximation and details coefficient of decomposition (left) and reconstruction (right) discrete wavelet transform



(a)



(b)



(c)

Fig. 8 Signal with fault inception due to (a) short circuit (b) capacitor switching (c) lightning

Statistical Results

Based on the results, normal signal shows high skewness and kurtosis value which indicates outliers' data in the sample.

Under normal condition, the values of the skewness and kurtosis are supposedly low, close to zero due to no extreme event induced in the waveform. These high values in the features are due to border distortion effect produced when the waveform analysis reduced into one cycle as shown in Fig. 9. Border distortion can be ignored as it does not indicate any significant event. Border distortion effects are very common in many finite-length non-stationary signal analysis and processing approaches in time-frequency analysis [22]. The formation of the distortion occurred at the starting and ending of finite length signal. At the end of the signal, the convoluting window extends partially on the signal domain, in which abnormal coefficients arise and corrupted the transform. However, the distorted border gives significant influence that leads to situation of false indication [23–26]. Therefore, the threshold value was implemented for normal waveform to truncate the unwanted border distortion. The threshold line was set to be one as shown in Fig. 9.

WT extracted the energy, skewness and kurtosis of each approximation and detail coefficient respectively. Table 3 illustrates the results of four different cases from the waveform. The energy approximation at level 4 (A4) and energy detail coefficient at level 1 to 4 (D1, D2, D3, & D4) were shown in the table for comparative study. Based on the details coefficient production, energy of D1 shows the best performance due the lowest noises generated from high pass filter. From the energy of D1, lightning gives the highest value (yellow) while short circuit is the lowest value (blue). The lightning stroke gives an impactful magnitude towards energy production. As the detail coefficient increases, the energy detail increases. This finding is observed for lightning cases only and not for switching or short circuit cases. Therefore, the D1 energy can be used as the behaviour indicator of lightning, switching and short circuit in terms of magnitude.

For skewness, lightning lgives the highest skewed tail to the right with the value of 2.2212 as compared with the switching and short circuit. Short circuit signal gives the lowest value at 0.1907. From the observation, it is found that the faulty phase produces tail skewed to the right. The most impactful voltage causes the leniency tail skewed to the right. While the healthier phase (normal) produces the leniency tail to the left. For the kurtosis, lightning outcome gives the highest magnitude index compared to switching and short circuit. Data sets with high kurtosis tend to have a distinct peak close to the mean, turn down quite fast, and contain deep tails. From Table 3, it can be summarized that lightning fault gives significant high values in terms of energy, skewness, and kurtosis compared to switching and short circuit faults.

To validate the result, mean square error (MSE) was evaluated for each cases to compare the signals with the normal condition. The MSE was calculated based on D1 coefficient. From Table 4, lightning fault results in the highest MSE energy, skewness, and kurtosis values. On the other hand, switching fault gives the lowest MSE in terms of skewness and energy produced while short circuit fault gives the lowest MSE for kurtosis. The inconsistent results for short circuit and switching can be due to noises contain in the extracted signals thus may led to wrong interpretation of prediction. Ultimately, only lightning event contains significant features that can perform its behaviour based on D1 coefficient.

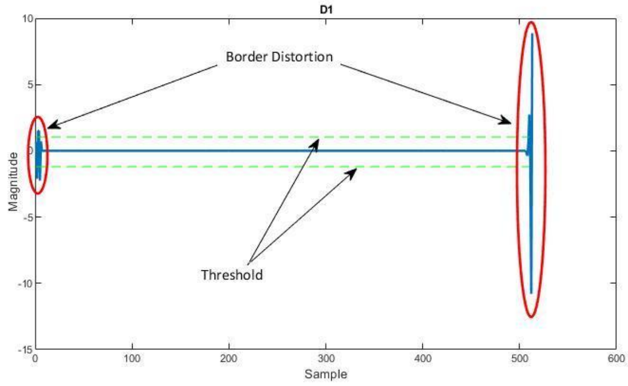


Fig. 9 Border distortion effect normal discrete wavelet waveform

Table. 3 Energy, skewness, and kurtosis of details coefficient

Types	A4	D4	D3	D2	D1
			Energy (kJ)		
Normal	99.9984	0	0	0.0005	**0.0011**
Switching	99.4726	0.0162	0.0387	0.2502	**0.2223**
Lightning	62.0046	20.8609	13.2167	3.2119	**0.7060**
Short circuit	99.686	0.0225	0.0513	0.2216	**0.0560**
			Skewness		
Normal	0.0037	-0.0771	-5.4770	-3.0520	-3.8507
Switching	-0.0181	1.7791	-2.2111	2.2871	**0.3959**
Lightning	0.00593	2.0733	2.0639	-1.3314	**2.2212**
Short circuit	0.1943	1.3776	-2.4494	2.1713	**0.1907**
			Kurtosis		
Normal	1.5013	4.2339	12.3255	26.5364	**126.2579**
Switching	1.4977	23.8850	56.9576	85.6443	**131.1097**
Lightning	1.5776	31.8698	65.7891	101.2576	**199.8650**
Short circuit	1.9611	33.1960	62.1996	86.1694	**131.8057**

Table. 4 MSE of D1 coefficient of different fault causes

Types	MSE		
	Energy	Skewness	Kurtosis
Switching	0.0489	18.0336	23.5400
Lightning	0.4979	36.8680	5.4180e+03
Short circuit	0.0025	16.3329	30.7781

IV. CONCLUSIONS

This paper describes new features extracted from the wavelet transform to detect fault causes whether due to lightning, switching, and short circuit. The presented techniques extracted the energy, skewness, and kurtosis features which enable to identify the types of faults based on their distinct value. It can be concluded that lightning fault features gives a significant value compared to switching and short circuit based on D1 extraction. On the other hand, switching and short circuit faults show inconsistent results that may led to wrong interpretation prediction and need to be explored further. As for validation, the result of MSE values calculated also indicated that lightning contains a significant high value.

In this study, it is shown that the existence of border distortion will reduce the accuracy of the extracted signals. Threshold technique is adopted to overcome the border distortion. However, the evaluation is based on D1 coefficient without considering noises and border effect. In future work, the behaviour of fault causes can be identified further by setting the pre-determine threshold (THD) to acknowledge the features. In addition, details coefficient and approximation can also be considered. All the features acquisition can be applied to reveal the fault causes signature in distribution system and become the novelty of this research. Lastly, classification types of fault can be implemented in the future based on the MSE prediction value.

ACKNOWLEDGMENTS

The authors would like to thank Universiti Tenaga Nasional through an internal research grant of J510050789 for the financial support to this research. Special thanks to those who contributed to this project directly or indirectly.

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