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Extract Fault Signal via DWT and Penetration of SVM for Fault Classification at Power System Transmission

Azriyenni Azhari Zakri
Department of Electrical Engineering
Faculty of Engineering
Universitas Riau
Pekanbaru, Indonesia
azriyenni@eng.unri.ac.id
(IEEE Member: 92012627)

Syukri Darmawan
Department of Electrical Engineering
Faculty of Engineering
Universitas Riau
Pekanbaru, Indonesia
syukri.darmawan@student.unri.ac.id

Jafaru Usman
Department of Electrical & Electronic Engineering
Faculty of Engineering
University of Maiduguri
Borno State, Nigeria
(IEEE Member: 92148421)

Iswadi Hasyim Rosma
Department of Electrical Engineering
Faculty of Engineering
Universitas Riau
Pekanbaru, Indonesia
(IEEE Member: 92506698)

Boy Ihsan
Department of Electrical Engineering
Faculty of Engineering
Universitas Riau
Pekanbaru, Indonesia

***Abstract* — Power transmission lines are extremely important for the power system to deliver energy of electricity from the plant to the load. The short circuit of fault often occurs in the transmission line and may lead to disconnecting the power supply to the load. This study implements a hybrid technique that is Discrete Wavelet Transformation (DWT) and Support Vector Machine (SVM) for classification of fault in the transmission line. The DWT was created to extract the detailed signal of transient D8 and D9 (order of 4) at 50 kHz for sampling frequency. The value of Root Mean Square (RMS) will be determined by the coefficients D8 and D9 for training and test data using SVM technique. Furthermore, SVM is utilized to detect the fault for each phase and the ground is discovered in the type of fault. The SVM technique has been run using parameter C and kernel scale to achieve the great results of classification of the fault. Type of simulating fault has a variation of location of the fault, fault of resistance and initial angle. The training and test data run for the Test System of Riau, Indonesia. The test result for the classification of fault reaches the highest accuracy of 100%.**

Keywords— DWT, fault, SVM, detection, classification

I. Introduction

Transmission line is vital component for the electric power system to send electrical energy from a power station to distribution network connected then to load. A fault that occurs in the transmission line can be expected to result in the termination of power supply in the distribution system which gives rise to blackout at the consumer terminals [1]. The short circuit fault may occur asymmetrically and symmetrically [2]. Asymmetric fault comprises of one-phase fault to ground, phase to phase and two phases to ground. While symmetrical fault that is three phase fault. Any types of short-circuit fault that occur has different characteristics for current and voltage. Therefore, any short circuit fault that occurs on the transmission line must know about the type and how to solve it differently.

The application of hybrid technique for the classification of short circuit faults is presented in this study. This hybrid technique is a combination of Discrete Wavelet Transformation (DWT) and Support Vector Machine (SVM) techniques. Wavelet Transforms (WT) has advantages of Fourier Transforms (FT), which is limited information on the frequency domain. The information obtained from wavelet transforms is dedicated to frequency domain and time domain [3].

WT are commonly used in determining the type of fault that occurs in the transmission line [4]. Practically, the study using DWT is more widely used than Continuous Wavelet Transformation (CWT) to decode voltage and current signals as to show signal characteristics in some frequency bands [5, 6]. Previous researchers have carried out a study using WT for the classification of fault on parallel transmission lines. They utilized DWT have mother wavelet (order of 8) at a sampling frequency of 12.5 kHz. The Authors were able to classify the type of fault in parallel transmission line using ANN techniques [7].

Other researchers conducted DWT study with mother wavelet daubechies (order of 4) at a sampling frequency of 200 kHz using Back-propagation Neural Network (BNN). Result obtained in Mean Square Error (MSE) is 0.03721 and Mean Absolute Error (MAE) is 0.11952 for each type of the fault in parallel transmission line [8]. Another study also introduced the sum of absolute values of the detail coefficients of levels 8 and 9 as SVM input [9]. Data processing generated by DWT will serve as input in using the SVM technique for classification of the fault. The SVM technique for the type of fault is expected a high degree of accuracy compared to other intelligent techniques, such as; Artificial Neural Network (ANN), Probabilistic Neural Network (PNN) and Adaptive Neural Fuzzy Inference System (ANFIS).

This research will be conducted to extract D8 and D9 values using DWT with mother wavelet type daubechies (order of 4) at 50 kHz sampling frequency. Root Mean Square (RMS) value will be derived with the coefficients D8 and D9 for training and test data via SVM technique. The SVM will be run by the parameter box constraint C for classification of the fault that will be implemented by simulating software for test system Riau, Indonesia. The targeted results of the simulations are expected to achieve the great accuracy of the classification of the fault.

II. Methodology

A. DWT

DWT has ability to analyse various types of the fault with information obtained rather than the frequency domain and time domain. The DWT is very useful in detecting and processing various faults because of sensitive to signal irregularity [10]. The wavelet transform can be divided into two types, that is; DWT and Continuous Wavelet Transforms (CWT). The CWT is the sum of signals over time multiplied by the scale and position of the wavelet function as shown in equations (1) and (2) [11]:

$$C\left(scale, position\right) = \int_{-\infty}^{\infty} f\left(t\right)\psi_{scale,\,position}\left(t\right)dt \tag{1}$$

$$T\left(scale, position\right) = \int_{-\infty}^{\infty} x\left(t\right)\psi^{*}_{scale,\,position}\left(t\right)dt \tag{2}$$

CWT has many coefficients WT is a function as a scale and position. This gives birth to result data to be redundant. The DWT have a couple of samples of WT of coefficients were taken from DWT to reduce the excess of coefficients from CWT. DWT is utilized to analyse wave signals efficiently and accurately. The DWT will be implemented using a filter using Mallat algorithm. DWT is divided into two wave signals i.e; filter techniques and down sampling operations. The high-pass filter technique generates additional signals with high frequency. The low-pass filters produce different signals with low frequency. After that, the data will be managed down sampling operation. So it only takes half of each data obtained before [10]. In Fig. 1, we can refer to the schematic of the signal processing using DWT.

The high frequency signals are called details and signals with low frequencies called approximations. The process of decomposition by iteration using of approximation of the data obtained previously. It will be decomposed to generate new approximation and detail data. Fig. 2 shows in the scheme of the decomposition iteration process, to get a new wave signal. It will be made by summing the approximation data and detail data.

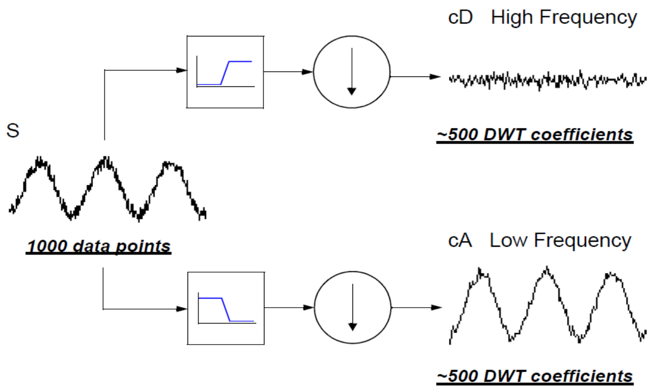

Fig. 1. Signal processing DWT.

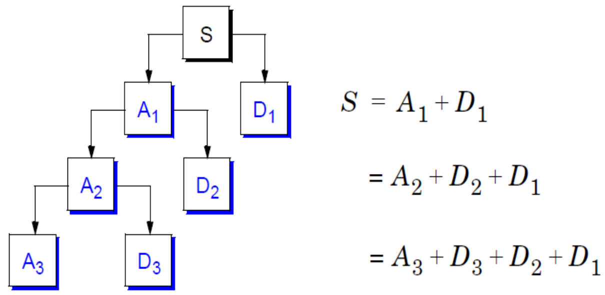

Fig. 2. Iteration of DWT the decomposition.

The more decomposition process, the signal can be split into many low-resolution components. Accordingly, the lower frequency component filter process will be run continuously. Table I indicates the decomposition of wavelet level 9 for a single cycle after the fault with a sampling frequency of 50 kHz [9].

TABLE I. The Wavelet Decomposition Order

Level	Approximation	Detail
1	0 – 12.5 kHz	12.5 – 25 kHz
2	0 – 6.25 kHz	6.25 – 12.5 kHz
3	0 – 3.125 kHz	3.125 – 6.25 kHz
4	0 – 1.563 kHz	1.563 – 3.125 kHz
5	0 – 781 Hz	781 – 1.563 kHz
6	0 – 391 Hz	391 – 781 Hz
7	0 – 195 Hz	195 – 391 Hz
8	0 – 98 Hz	98 – 195 Hz
9	0 – 49 Hz	49 – 98 Hz

B. SVM

SVM is a learning system that uses a hypothetical linear function in a high-dimensional space and is trained with algorithms based on bias learning optimization theory. The main purpose of this algorithm is to establish optimal separating hyper-plane, which functions optimum separation that can be used as a classification.

Data on the boundary field are called support vector. Fig. 3 shows a pair of parallel bounding plates separating the two data classes. Fig. 3 shows data living together with the delimiter field called support vector. Two classes can be isolated by a pair of parallel bounding planes. $|b|/\|\mathbf{w}\|$ are the spacing plane distance perpendicular from the center point of the coordinate and $\|\mathbf{w}\|$ is the Euclidean distance of $\mathbf{w}$.

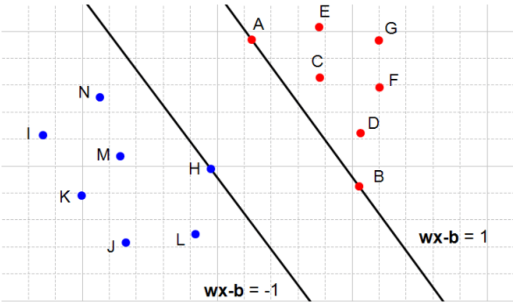

Fig. 3. Two parallel bounding plates are separating each class.

The first delimiter field limits the first class when the second delimiting area limits the second class, the formula expressed in equation (3) can be used [13]:

$$\begin{aligned} \mathbf{x}_i\mathbf{w} + b &\geq 1, y_i = 1 \\ \mathbf{x}_i\mathbf{w} + b &\geq -1, y_i = -1 \end{aligned} \tag{3}$$

Where, $\mathbf{w}$ is a normal plane and b is an alternate field position against the coordinate center. The marginal value between the bounding planes is from the formula of spacing to the center point, as follows [14]:

$$m = \frac{2}{\|\mathbf{w}\|} \tag{4}$$

The value of this margin will be maximized to satisfy equation (2), by multiplying b and $\mathbf{w}$, it will result in a marginal value multiplied by the same constant. The constraint in equation (2) is a scaling that can be satisfied by rescaling b and $\mathbf{w}$. therefore, to maximize $1/\|\mathbf{w}\|$ equals to minimize $\|\mathbf{w}\|^2$. The two limiting fields of equation (2) will be represented by the inequality expressed in equation (5), subsequently [14]:

$$y_i\left(\mathbf{x}_i\mathbf{w} + b\right) \geq 1 \tag{5}$$

The best separation of the field line is the largest margin value can be formulated into constraint optimization, as follows [15]:

$$\min \frac{1}{2}\|\mathbf{w}\|^2 \tag{6}$$

To classify data linearly using SVM formula, in order that added variable called soft margin hyper-plane. Thus, the best separator formula becomes [14]:

$$\min \frac{1}{2}\|\mathbf{w}\|^2 + C\left(\sum_{i=1}^{n} \xi_i\right) \tag{7}$$

$$\text{With, } y_i\left(\mathbf{x}_i\mathbf{w} + b\right) \geq 1 - \xi_i, \xi_i \geq 0$$

Parameter C is determined from the penalty due to errors in the data classification and the value is determined by the user. The roles of parameter C minimize training errors and reduce model complexity. The parameter C of SVM is also commonly called box constraint [14]. Fig. 4 shows the training scheme using SVM to detect and classify of the fault at each phase and ground. By knowing the existence of fault at every phase and ground, hence can be determined kind of short circuit fault that happened.

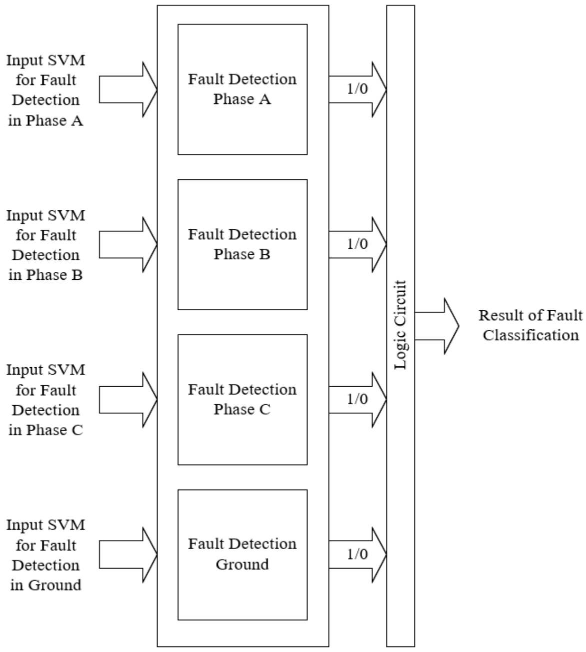

Fig. 4. The classification of fault using SVM.

To calculate the percentage of accuracy for classification of the fault, the formula expressed in equation (8) can be used [6]:

$$\text{Classification accuracy} = \frac{\text{Accurate fault classification}}{\text{Number of samples tested}} \times 100\% \tag{8}$$

C. Power System Transmission

Transmission system used comes from the data of PT. PLN (Persero). The transmission system used is composed of three buses that are; Bus KP, Bus BG and Bus GS. The transmission line system is currently under a voltage of 150 kV and a frequency of 50 Hz. In the transmission line between the Bus KP and the short circuit fault at Bus GS, as depicted in Fig. 5.

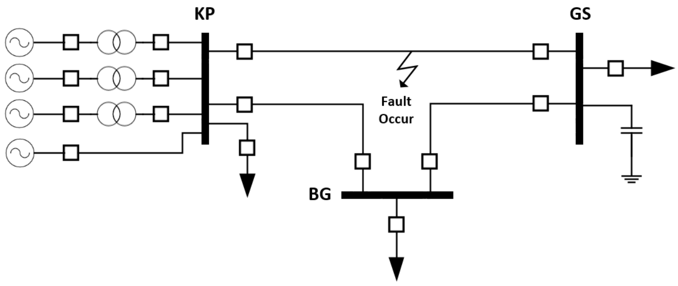

Fig. 5. Single line diagram transmission system

The substation KP consists of four power sources. The parameter used for each generator as given in Table II. Afterward, Table III shows the power transformer parameters connected to the generator. Table IV is the transmission line parameter employed to each connection from bus to bus. The length of a transmission line from Bus KP to Bus GS is 64 km, Bus KP to Bus BG is 18.19 km and Bus BG to GS is 46.09 km. Each bus is placed under a load with the parameters as in Table V. On the bus GS found a capacitor bank with a capacity of 50 MVAR.

TABLE II. PARAMETER OF GENERATOR

Generator	MVA Short Circuit (MVA)	V_{RMS} (kV)	Frequency (Hz)	X/R
1, 2, 3	209.25	11	50	13
4	1260.85	150	50	5

TABLE III. PARAMETER OF TRANSFORMER

Parameter	High Voltage Side	Low Voltage Side
Rate Power	60 MVA	
Nominal Frequency	50 Hz	
Rated Voltage	150 kV	11 kV
Leakage Resistance	0.5 p.u.	0.5 p.u.
Leakage Reactance	0.5 p.u.	0.5 p.u.
Connection	Y	Y

TABLE IV. PARAMETER OF TRANSMISISION LINES

Sequence	Resistance (Ω/km)	Inductance (Ω/km)	Suceptance (µS/km)
Positive/Negative	0.079	0.389	2.95e-6
Zero	0.305	1.029	1.884e-6

TABLE V. PARAMETER OF LOAD

Bus	Active Power (MW)	Reactive Power (MVAr)
KP	17.95	5.8
BG	48.032	13.2
GS	114.788	26.9

III. RESULT

Data simulation is run with discrete type over 0.00002 s in each sample. After the fault occurs, one cycle current wave is used as DWT input with the number of samples 1 / (0.00002 * 50) = 1000 sample data. The simulated short-circuit fault is one-phase to ground (A-G, B-G, C-G), phase to phase (A-B, A-C, B-C), two phase to ground (A-B-G, A-C-G, B-C-G) and three-phase (A-B-C) [17].

A. System of Simulation

Some parameters used to obtain the training data and test data of the simulation have parameters as saw in Table VI. The resistance of the fault is 10 Ω.

TABLE VI. PARAMETER FOR TRAINING DATA AND TEST DATA

Parameter	Training Data	Test Data
Fault Distance (%)	0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100	5, 15, 25, 35, 45, 55, 65, 75, 85, 95
Fault Resistance (Ω)	10, 20, 35, 50, 70, 100, 150	8, 25, 45, 65, 85, 110, 140
Fault Inception Angle (°)	10, 20, 30, 40, 50, 60, 70, 80, 90	5, 11, 17, 24, 45, 65, 88

The number of simulations performed to obtain the training data is as much as 6930 data (10 faults * 11 fault distances * 7 fault resistances * 9 FIA). The number of simulations performed to obtain the test data is as much as 4900 data (10 faults * 10 fault distances * 7 faults of resistances * 7 FIA). The result of current has been run on the Bus KP becomes reference for the phase to ground (AG) of a short circuit. The fault distances with different points with 10% increments, resistance of fault 35 Ω and FIA 50 ° can be seen in Fig. 6.

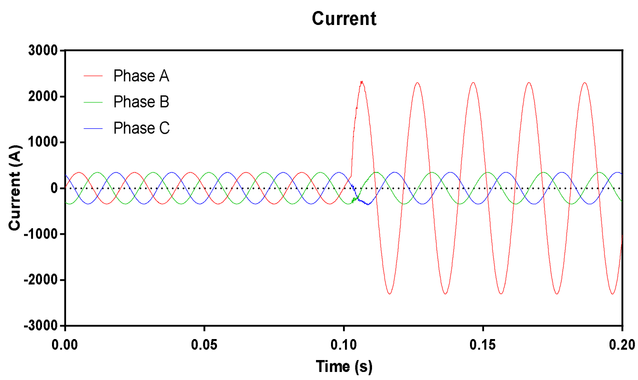

Fig. 6. The simulation fault current at bus KP for one phase to ground.

B. Processing Data

The fault current occurs in a single cycle (post fault) is processed using mother wavelet for daubechies order of 4 (db 4) at level 9. Data processing db 4 are run db 4 is very effective for analysis of transient signals [3, 4, 7]. Fig. 7 presents the results of data processing using DWT taken at the level 8 detail (D8) and detail level 9 (D9). The results of simulation training data and test data are run using DWT. The data on detail D8 and D9 of transient currents for one cycle after the fault occurs is done by calculating the Root Mean Square (RMS). This RMS value as input is detection of the fault on every phase using SVM technique. Furthermore, for ground detection is done by adding the current of each phase and divided by three as follows [2, 16]:

$$I_0 = \frac{I_a + I_b + I_c}{3} \quad (7)$$

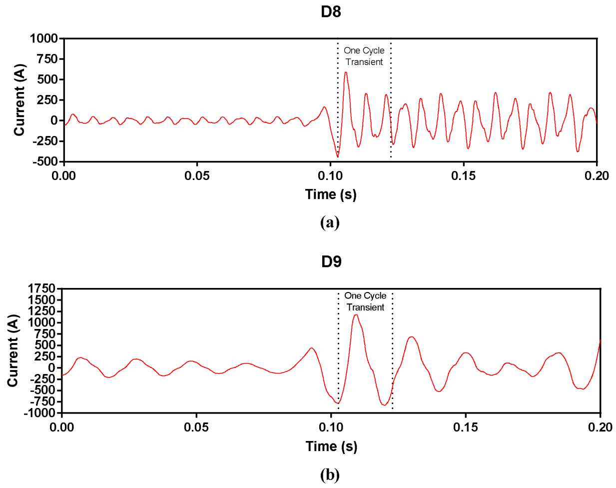

Fig. 7. DWT results in detail at: (a) level 8, (b) level of 9

C. *Detection of Short Circuit Fault*

The RMS detail of D8 and D9 for each phase and ground current is used as input SVM to obtain hyper-plane function. Parameter SVM is utilized to the parameter box constraint C value is 1 and kernel scale value is 0.35. Hyper-plane obtained from SVM training using the input value of training data. In Fig. 8 (a) is seen that the hyper-plane obtained from the SVM training for phase A. Then Fig. 8 (b) shows the results of the hyper-plane test data obtained from the previous test.

Fig. 8 (b) is data that has been verified by SVM for the detection of fault on phase A which does not pass through the hyper-plane. The result of the test is just an accurate value in establishing the presence or not of the fault in phase A. Table VII presents the classification of fault for test data by SVM with input data D8 and D9. The test result of classification of the fault achieved 100% accuracy (maximum value) for each type of the fault.

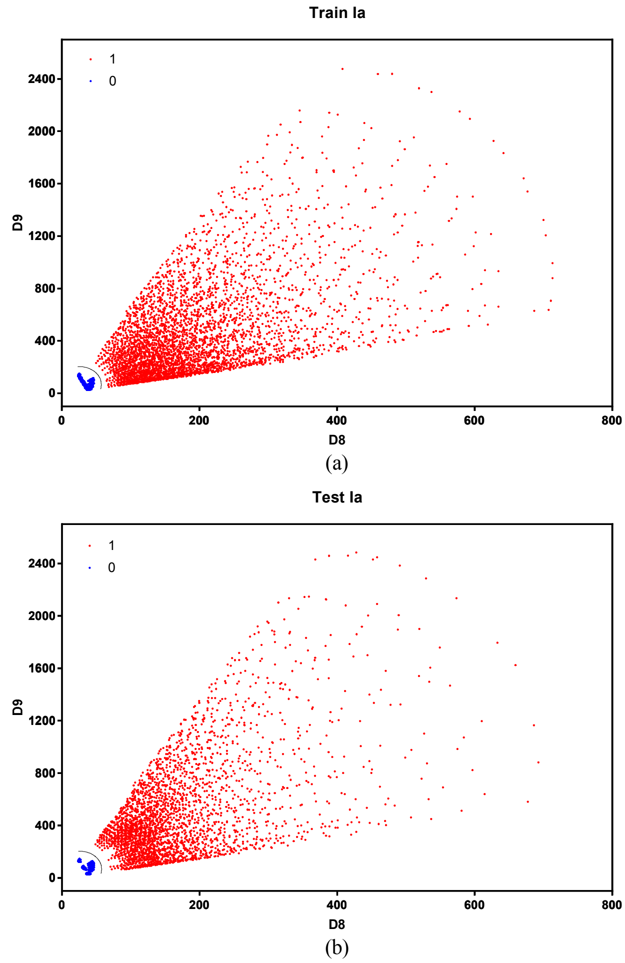

Fig. 8. Classification of fault using SVM on: (a) training data, (b) test data.

TABLE VII. THE TEST RESULT FOR CLASSIFICATION OF THE FAULT

Type of Fault	Number of Test Data	Number of Test Sample (T)	Number of Test Sample (F)	Accuracy (%)
L-G (A-G, B-G, C-G)	1470	1470	0	100
L-L (A-B, A-C, B-C)	1470	1470	0	100
L-L-G (A-B-G, A-C-G, B-C-G)	1470	1470	0	100
L-L-L (A-B-C)	490	490	0	100

IV. CONCLUSION

In this study has penetrated the classification of short-circuit fault with the great value. The technique has been applied to DWT to extract the detail of D8 and D9. This simulation is executed during a single cycle after the fault occurs for each current phase and ground. Afterwards, RMS value calculated for coefficient D8 and D9 for training data and test data with distance fault, the fault resistance and FIA as input of SVM. The parameter of SVM used box constraint and kernel scale to produce a good hyper-plane function. The simulation results for the classification of fault are achieved with a maximum accuracy of 100%.

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