Discrete Wavelet Transform and Support Vector Machines Algorithm for Classification of Fault Types on Transmission Line

K. Kunadumrongrath and A. Ngaopitakkul, *Member, IAENG*

***Abstract*— This paper proposes a new technique using discrete wavelet transform (DWT) and support vector machines (SVM) to classify the fault types on transmission systems. The DWT is used to detect the high frequency components from fault signals. Positive sequence current signals are used in fault detection decision algorithm. The variations of first scale high frequency component that detects fault are used as an input for the SVM. Various cases studies based on Thailand electricity transmission systems have been investigated so that the algorithm can be implemented. SVM is also compared with the comparison of the coefficients DWT technique as well as back-propagation neural network algorithm. The proposed method gives satisfactory accuracy, and will be very useful in the development of a modern protection scheme for electrical power transmission systems.**

***Index Terms*—Wavelet Transform, Fault Classification, Transmission Line, Support Vector Machines**

I. Introduction

Protecting transmission line is an important task to safeguard electric power system. The precision protection scheme is necessary to be detected, classified and located accurately, and cleared as soon as possible. The development in power system protection technology has been progressed, especially in recent years. In several research papers, the fault classification can be obtained by employing trial and error method [1-5]. In previous research works [3], by considering the pattern of the spectra, the comparison of the coefficients from first scale that can detect fault is considered. The division algorithm between the maximum coefficients of DWT at ¼ cycle of phase A, B, C is performed. For identifying the phase with fault appearance, the comparisons of the maximum ratio obtained from division algorithm have been performed so that the types of fault can be analysed. Although the wavelet transform is very effective in detecting transient signals generated by the faults, but the wavelet transform may not be adequate to complete characterization.

In addition, artificial intelligence (AI) has been reported in the literature for fault classification [6-11]. In several research papers, the back-propagation neural network (BPNN) [8] is employed as well as Probabilistic neural network in order to identify types of fault on the transmission line. Even if artificial neural network algorithm can give precise results for fault types, it is partly limited by the slow training performance. This drawback of artificial neural networks should be improved, otherwise the other types of artificial intelligence should be developed instead. It is interesting to investigate an appropriate support vector machines if the fault types on the transmission line can be identified using wavelet transform and support vector machines for being included in newly-developed protection systems.

Therefore, this paper presents a development of a new decision algorithm used in the protective relays in order to classify types of fault along the transmission systems. The fault conditions are simulated using ATP/EMTP. The current waveforms obtained from the simulation, then, are extracted using the DWT. The validity of the proposed algorithm is tested with various fault inception angles, fault locations and faulty phases. In addition, the construction of the decision algorithm is detailed and implemented with various case studies based on Thailand electricity transmission systems. Moreover, the results from the proposed algorithm are compared with those from the trial-error [3] and the BPNN [8] in order to show the advantage of the proposed method.

II. Power System Simulation using EMTP

The ATP/EMTP is used to simulate fault signals at a sampling rate of 200 kHz. The fault types are chosen based on the Thailand's transmission system as shown in Figure 1. Fault patterns in the simulations are performed with various changes in system parameters as follows:

- Fault types considered in this study are : single line to ground (SLG : AG, BG, CG), double-line to ground (DLG : ABG, BCG, CAG), line to line (L-L : AB, BC, CA) and three-phase fault (3-P : ABC).
- Fault locations are varied from 10% to 90%, with the increase of 10% of the transmission line length measured from the bus MM3.
- Inception angle on a voltage waveform is varied between 0°-330°, with the increasing step of 30°. Phase A is used as a reference.
- Fault resistance is equal to 10 Ω.

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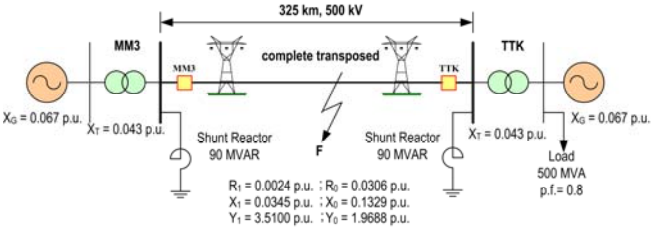

Fig. 1 The system used in simulation studies [12].

The example of simulated fault signals by ATP/EMTP is illustrated in Figure 2. This is a fault occurring in phase A to ground at 30% of transmission line length measured from the bus MM3 as depicted in Figure 1. The fault signals generated using ATP/EMTP are interfaced to MATLAB for the fault detection algorithm.

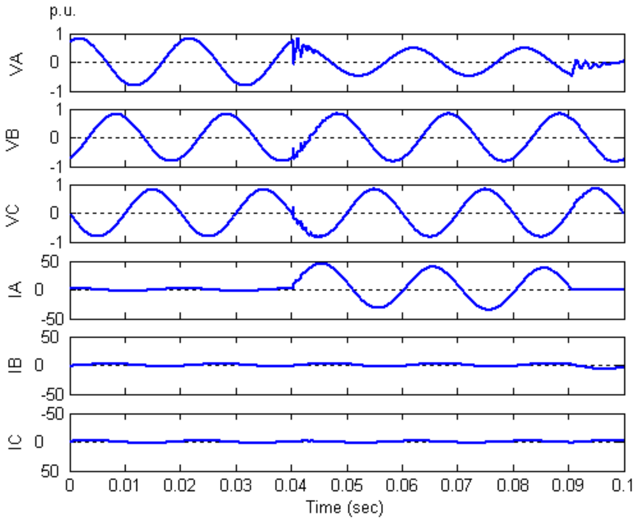

Fig. 2 Example of simulated fault signals by ATP/EMTP for AG fault at sending end.

The Clark's transformation matrix is employed for calculating the positive sequence and zero sequence of currents. With several trial and error processes, the fault detection decision algorithm on the basis of computer programming technique is constructed as shown in Fig. 3.

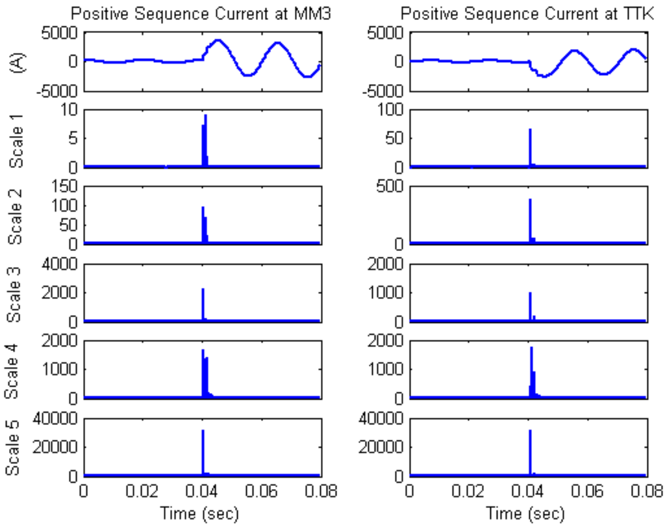

Fig. 3. Wavelet transform from scale 1 to 5 for the positive sequence of current signal shown in Fig. 2.

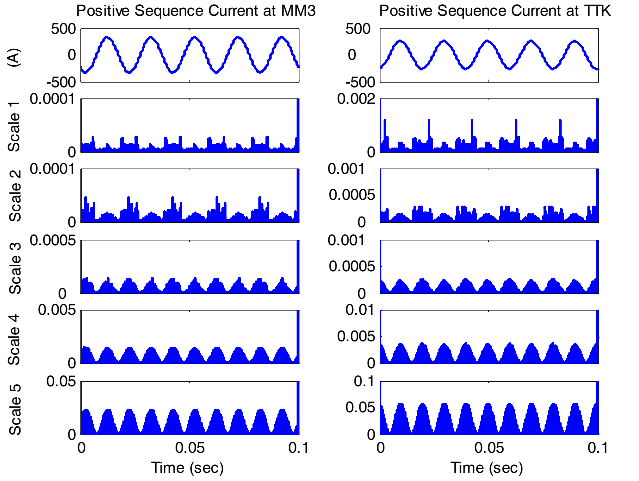

Fig. 4. Wavelet transform from scale 1 to 5 for the positive sequence of current signal in normal condition.

The mother wavelet daubechies4 (db4) [3, 8, 13] is employed to decompose high frequency components from the positive sequence current signals. Fault detection decision algorithm [3, 8] is proceeded using positive sequence current signal. Coefficients obtained using DWT of signals are squared so that the abrupt change in the spectra can be clearly found, and it is clearly seen that the coefficients of high frequency components, when fault occurs, have a sudden change compared with those before an occurrence of the faults as shown in Fig. 3. The fault detection decision algorithm has been proposed that if coefficients of any scales are change around five times before an occurrence of the faults, there are faults occurring on transmission lines.

From Fig. 4., the coefficient in each scale of the wavelet transform does not clearly change then it presumes that these signals are in normal operating condition. By performing many simulations, it has been found that the coefficient in scale 1 from DWT seems enough to indicate the fault inception on the single circuit transmission line. As a result, it is unnecessary to use other coefficients from higher scales in this algorithm, and the coefficients in scale 1 from DWT are used in training processes for the neural networks later.

III. Decision Algorithm and Result

From the simulated signals, DWT is applied to the quarter cycle of voltage and current waveforms after the fault inception. The coefficients of scale 1 obtained using the DWT are used for SVM. The basic idea of SVM is to map the training data from the input space into a higher dimensional feature space via kernel function. In this feature space optimal hyper plane is determined to maximize the generalization ability of the classifier.

Before the training process, input data are normalized and divided into 720 sets for training and 360 sets for test. A structure of the support vector machines consists of 4 inputs, 5 SVM models and 1 output. The input patterns are maximum coefficients of DWT at ¼ cycle of phase A, B, C and zero sequence for post-fault current waveforms as illustrated in Figure 5. The output variables of the support vector machines are designated as value range from 1 to 15, which corresponds to various types of fault as shown in Table 1.

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Table 1 Output of SVM for classifying the fault types

Models of SVM	Output of SVM	Classification of fault type	Types of fault
1	1	Phase A to ground fault	AG
	2	Phase B to ground fault	BG
	3	Other fault	NA
2	4	Phase C to ground fault	CG
	5	Phase A,B to ground fault	ABG
	6	Other fault	NA
3	7	Phase B,C to ground fault	CAG
	8	Phase C,A to ground fault	BCG
	9	Other fault	NA
4	10	Three phase fault	ABC
	11	Phase A to phase B fault	AB
	12	Other fault	NA
5	13	Phase C to phase A fault	CA
	14	Phase B to phase C fault	BC
	15	Other fault	NA

During training process, five SVM models are investigated and each model contains two fault types as shown in Table 1. For each SVM model, the adjusted parameters with minimum error are selected as the most appropriate parameters so that the obtained output is only determined as fault or other fault.

After the training process, case studies are varied so that the decision algorithm capability can be verified. The total numbers of the case studies are 360. Various case studies are performed with various types of faults at each location on the transmission line including the variation of fault inception angles and locations at each transmission lines as shown in Table 2 and Figure 6. In addition, the results obtained from the comparison of average accuracy among decision algorithm using the proposed technique, BPNN algorithm and decision algorithm using the comparison of the coefficients DWT which developed by Markming et al [3] are shown in Table 2. It is shown that the average accuracy of fault classification from the decision algorithm proposed in this paper is highly satisfactory. This is an improvement of the fault classification which is detected using the trial and error method developed by Markming et al [3] as well as BPNN [8].

IV. Conclusion

This paper proposed a new algorithm for fault classification on transmission lines, using DWT and SVM. Daubechies4 (db4) is employed as mother wavelet in order to decompose high frequency components from fault signals. Positive sequence current signal is used in fault detection. The coefficients detail of DWT at the first peak time that positive sequence current can detect fault, were performed as an input pattern of SVM in a decision algorithm. The results show clearly that the accuracy of the combination of discrete wavelet transform and support vector machines algorithm is highly accepted as shown in Table 2. The further work will be the improvement of the algorithm by taking into account the effects of other transmission line configurations, instance loop circuits or double circuits for the development of the practical protection system.

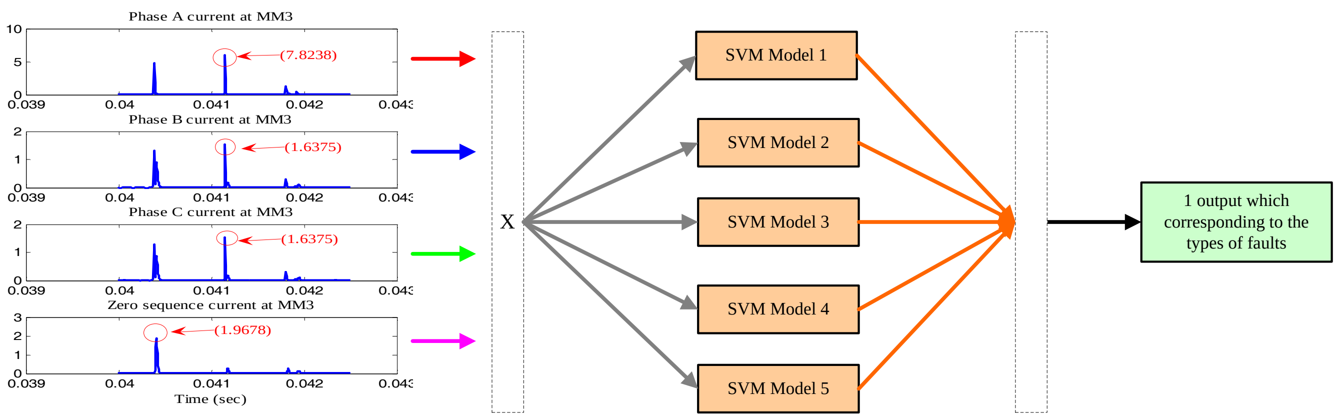

Fig. 5 Structure of SVM for classifying types of fault.

Table 2 summary of overall accuracy obtained from the proposed algorithms

Classification of the fault types	Number of Case Studies	Fault Classification		
		DWT and BPNN [8]	DWT and SVM	Trail and error method [3]
Single line to ground fault	108	100.00%	100%	100.00%
Double line to ground fault	108	98.12%	100%	42.59%
Line to line fault	108	100.00%	99.07%	100.00%
Three phase fault	36	97.22%	100%	97.22%
Average		98.83%	99.76%	83.33%

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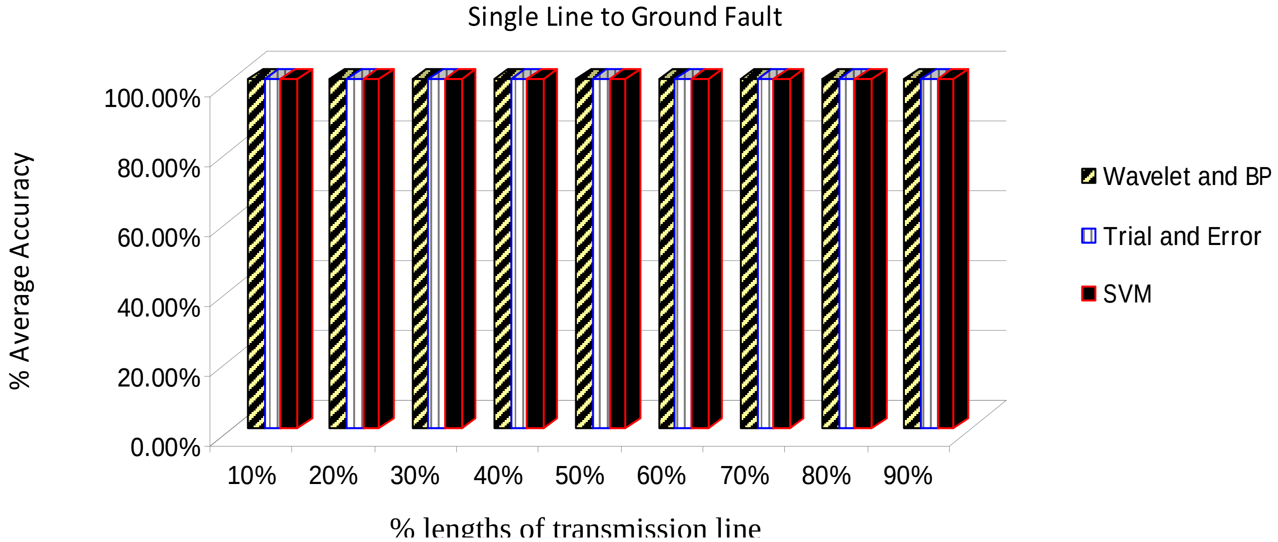
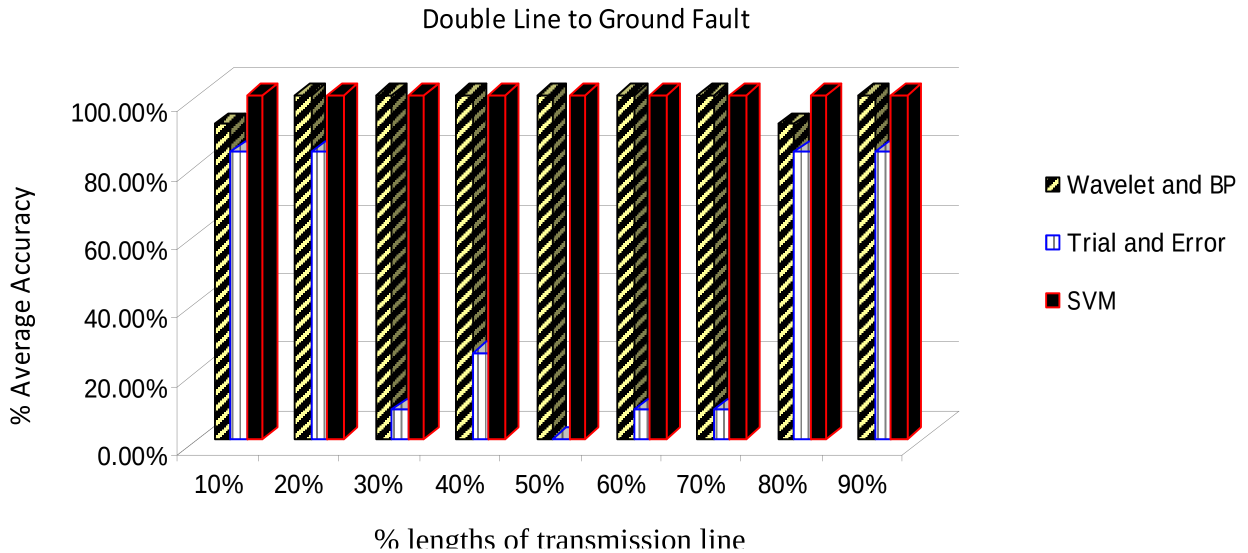
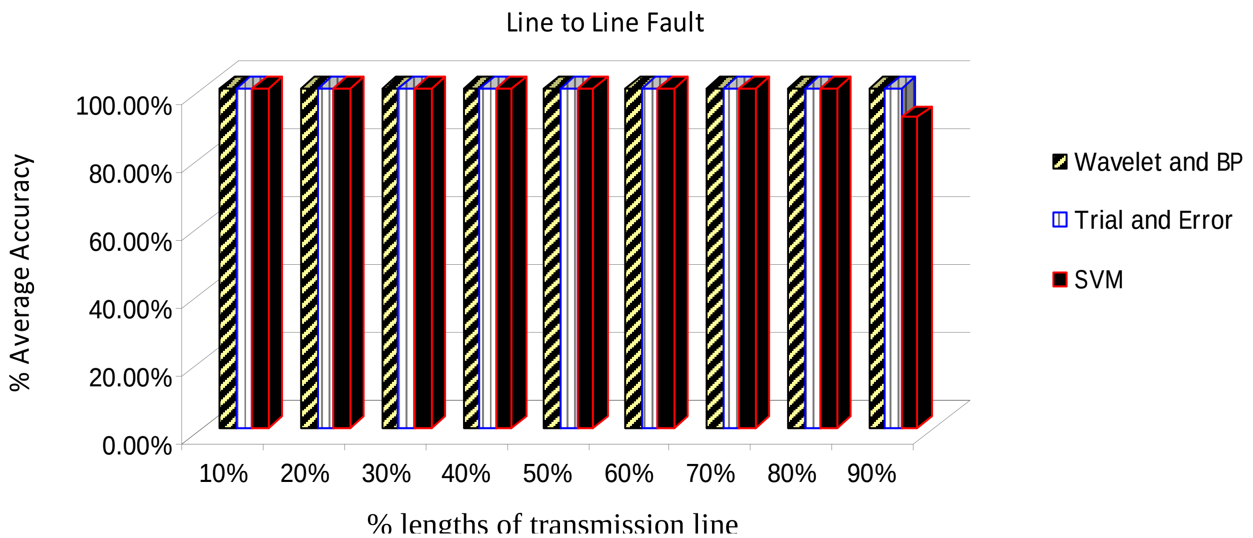


(a) In case of single line to ground fault



(b) In case of double line to ground fault



(c) In case of line to line fault

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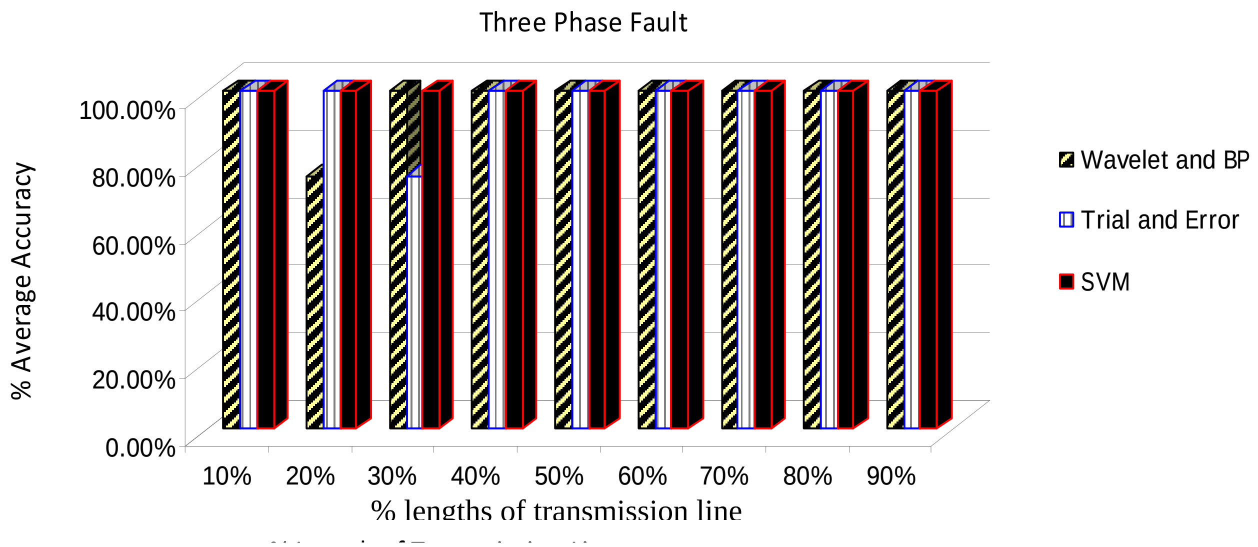

(d) In case of three phase fault

Fig 6. Comparison of average accuracy for fault classification at various lengths of the transmission lines that fault occurs

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