Identification of Fault Types for Single Circuit Transmission Line using Discrete Wavelet transform and Artificial Neural Networks

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***Abstract*—This paper proposes a new technique using discrete wavelet transform (DWT) and artificial neural network for fault classifications on single circuit transmission lines. Simulations and the training process for the artificial neural network are performed using ATP/EMTP and MATLAB. The mother wavelet daubechies4 (db4) is employed to decompose, high frequency component from these signals. Positive sequence current signals are used in fault detection decision algorithm. The variations of first scale high frequency component that detect fault are used as an input for the training pattern. Back-propagation (BP) neural network is also compared with the RBF neural network in this paper. The result is shown that an average accuracy values obtained from RBF gives satisfactory results with less training time, and will be very useful in the development of a power system protection scheme.**

***Index Terms*—Wavelet Transform, Fault Classification, Transmission Line, Artificial Neural Network, ATP/EMTP.**

I. Introduction

Protecting transmission lines is one important task to safeguard electric power systems. For a safe operation of 500kV power systems, the precision protection schemes need to be detected, classified and located accurately and cleared as fast as possible. The development in power system protection technology has progressed, especially in recent years. The method of symmetrical components is based on fault analysis for over 60 years in various protective relay applications [1]. During 1980s, the fault classification techniques have been proposed based on the variation of the voltage and current of the three phases [2]. During 1990s researcher had interesting in artificial neural networks (ANNs). ANNs are used for analysis and decide of relay due to it increase capability and process mimic the human brain's. However, there are still problems associated with hardware such as the lack of good analog memories, the limited number of interconnections.

By the end of the 1990s, the development in the algorithm for detecting the faults on the transmission lines has been progressed and results in transient based techniques [3]. It has been found that the wavelet transform is capable of investigating the transient signals generated in power system [4]. In several research papers, the fault current signals are decomposed into various scales of the wavelet transforms. By considering the pattern of the spectra [5-6], the fault diagnosis can be achieved. The fault classification can be obtained from employing trial and error method [5-6]. Although, the wavelet transform is very effective in detecting transient signals generated by the faults but it may not be adequate to complete characterization. In recent years, the neural networks developed rapidly and neural networks have been successfully applied in several fields. Normally, the algorithm uses neural networks to indicate the proper decision. It is interesting to investigate an appropriate neural network for being included in newly-developed protection systems.

Currently, there are many types of artificial neural networks, only a few of these neuron-based structures, paradigms actually, are being used commercially. Back-propagation neural network is probably the most well known and widely applied of the neural networks today. Because of back-propagation neural network has been used to solve almost all types of problems. However, back-propagation neural network is limited partly by the slow training performance. It should be improved this drawback of back-propagation neural network or the other types of neural networks should be developed instead. Radial basis function (RBF) neural network is the most commonly-used types of feed-forward network as well as the back-propagation neural network. As a result, Radial basis function (RBF) neural network is selected in order to compare with back-propagation neural network, and the results obtained from the decision algorithm are investigated. Hence, the objective of this paper is to consider studies of an artificial neural networks for the decision algorithm used for classify of fault type on single circuit transmission lines. The simulations, analysis and diagnosis are performed using ATP/EMTP and MATLAB on a PC Pentium IV 2.4 GHz 512 MB. It is noted that the discrete wavelet transform is employed in extracting the high frequency component contained in the fault currents. The construction of the decision algorithm is detailed and implemented with various case studies based on Thailand electricity transmission systems.

II. Wavelet Transform

Wavelet transform is a mathematical technique used in signal analysis. The advantage of the transform is that the band of analysis can be fine adjusted so that high frequency components and low frequency components can be detected

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precisely. Results obtained from the wavelet transform are shown on both the time domain and the frequency domain. The wavelet transform which has a change in the analysis scale by the factor of two is called discrete wavelet transform (DWT) as in Equation 1 [4].

$$DWT(m,n) = \frac{1}{\sqrt{2^m}} \sum_k f(k) \psi\left[\frac{n - k2^m}{2^m}\right] \tag{1}$$

where, $\psi\left[\frac{n-k2^m}{2^m}\right]$ = mother wavelet

III. Simulation

Artificial neural networks are an attempt to simulate the human brain's nonlinear and parallel processing capability for applications. ANNs, therefore, have necessitated learn relationships between cause and effect of data into orderly and informative patterns. As a result, ANNs requires fault signal samples from simulations to training and test processes. The ATP/EMTP [7] is used to simulate fault signals at a sampling rate 200 kHz (depending on the sampling time used in ATP/EMTP). The scheme under investigations is chosen based on the Thailand's transmission system as shown in Fig 1. Fault patterns in the simulations are performed with various changes in system parameters as follows:

- Fault types are under consideration, namely: single phase 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 increasing 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 equals to 10Ω.

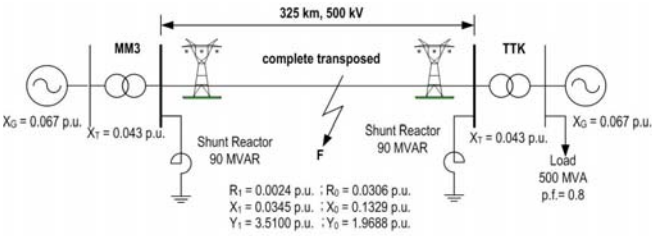

Fig. 1. The system used in simulation fault [6, 8]

The example of ATP/EMTP simulated fault signals for phase A to ground fault (AG) in each phase at the sending end (MM3) of the transmission lines is illustrated in Fig. 2. This is a fault occurring with phase A to ground fault (AG) at the length of 35% measured from the bus MM3 as in Fig. 1. The fault signals generated using ATP/EMTP are interfaced to the MATLAB/Simulink for a construction of fault diagnosis process.

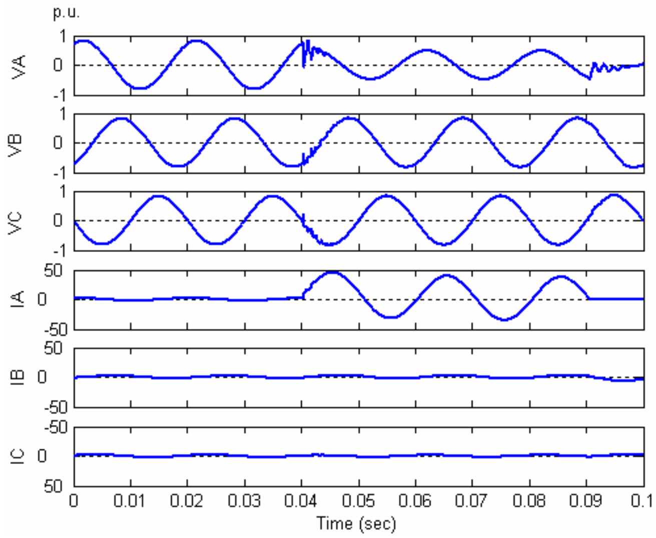

Fig. 2. The fault signals for AG fault at sending end of MM3

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. The mother wavelet daubechies4 (db4) [6, 9-10] is employed to decompose high frequency components from the positive sequence current signals. Fault detection decision algorithm is processed 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.

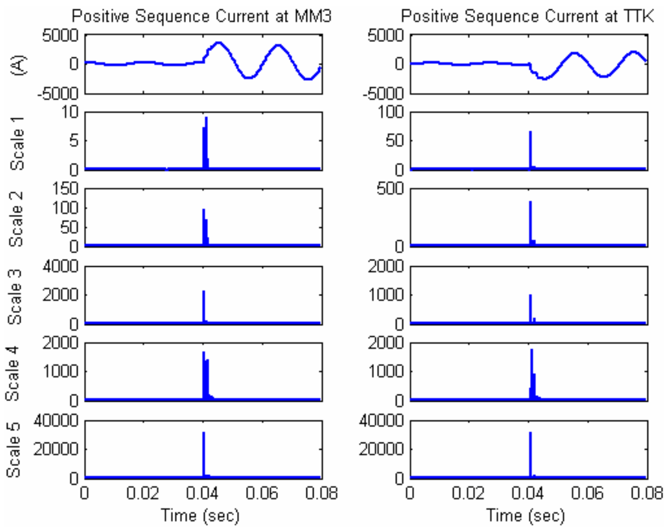

Fig. 3. Wavelet transform from scale 1 to 5 for the positive sequence of current signal shown in Fig. 2.

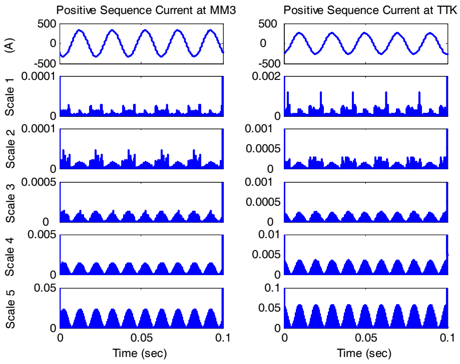

Fig. 4. Wavelet transform from scale 1 to 5 for the positive sequence of current signal in normal condition.

From Fig. 4., the coefficient in each scale of the wavelet transform do not clearly change then it presume that these signals are condition normal operating. 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.

IV. Decision Algorithm

From the simulated signals, DWT are applied to the quarter cycle of current waveforms after the fault inception. The coefficients of scale 1 obtained using the discrete wavelet transforms are used for training and test processes of the ANNs. A training process is performed using neural network toolboxes in MATLAB [11]. Before the training process, Input data sets are normalized and divided into 720 sets for training and 360 sets for tests. A structure of the artificial neural networks consists of 4 neurons for the inputs and 1 neuron for the output. The inputs patterns are maximum values of DWT at ¼ cycle of phase A, B, C and zero sequence for post-fault current waveforms as shown in Fig. 5. The output variables of the artificial neural networks are designated as either 0 or 1 which corresponding to phase A, B, C and ground (G) as shown in Table 1.

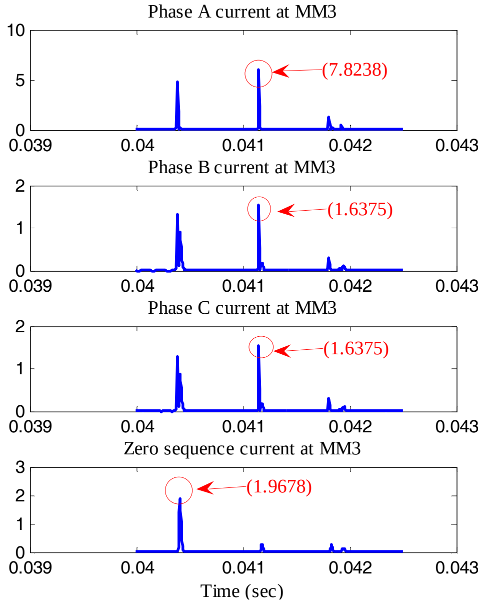

Fig. 5. Magnitude in scale 1 for post-fault all phase of current signal shown in Fig. 2.

Table 1 Output of ANNs for classify the fault types

Classify of fault type	A	B	C	G
Phase A to ground fault	1	0	0	1
Phase B to ground fault	0	1	0	1
Phase C to ground fault	0	0	1	1
Phase A,B to ground fault	1	1	0	1
Phase B,C to ground fault	0	1	1	1
Phase C,A to ground fault	1	0	1	1
Phase A to phase B fault	1	1	0	0
Phase B to phase C fault	0	1	1	0
Phase C to phase A fault	1	0	1	0
Three phase fault	1	1	1	0

A. Back-propagation Neural Networks.

In this paper, BP neural network consists of three layer of neurons [12] (Input, two-hidden, output) interconnected by weights. The inputs are fully connected to first hidden layer, each hidden layer is fully connected to the next, and the last hidden layer is fully connected to the outputs layer. In addition, hyperbolic tangent sigmoid functions are used as an activation function in all hidden layers while linear function is used as an activation function in output layers.

A training process for back-propagation neural network can be divided into three parts as follows [11-12]:

1. The feedforward input pattern, which has a propagation of data from the input layer to the hidden layer and finally to the output layer for calculating responses from input patterns illustrated in Equations 2 and 3.

$$a^2 = f^2\left(lw^{2,1} * f^1\left(iw^{1,1} * p + b^1\right) + b^2\right), \qquad (2)$$
$$o/p_{ANN} = f^3\left(lw^{3,2} * a^2 + b^3\right). \qquad (3)$$

where,
p is the input vector of ANNs
$iw^{1,1}$ is the weights between input and the first hidden layer
$lw^{2,1}$ is the weights between the first and the second hidden layers
$lw^{3,2}$ is the weights between the second hidden layer and output layers
b^1, b^2 are the bias in the first and the second hidden layers respectively
b^3 is the bias in output layers
f^1, f^2 are the activation functions (Hyperbolic tangent sigmoid function: tanh)
f^3 is the activation function (Linear function)

2. The back-propagation for the associated error between outputs of neural networks and target outputs; the error is fed to all neurons in the next lower layer, and also used to an adjustment of weights and bias.

3. The adjustment of the weights and bias by Levenberg-Marquardt (trainlm). This process is aimed at trying to match between the calculated outputs and the target outputs. Mean absolute percentage error (MAPE) as an index for efficiency determination of the back-propagation neural networks is computed by using Equation 4.

$$MAPE = \frac{1}{n} * \sum_{i=1}^{n} \left| \frac{o/p_{ANNi} - o/p_{TARGETi}}{o/p_{TARGETi}} \right| * 100\% \quad (4)$$

where, n is the number of test sets.

During training process [11-12], the weight and biases are adjusted by Levenberg-Marquardt (trainlm), and there are 20,000 iterations in order to compute the best value of MAPE. The number of neurons in both hidden layers is increased before repeating the cycle of the training process. The training procedure is stopped when reaching the final number of neurons for the first hidden layer or the MAPE of test sets is less than 0.5%. The training process can be summarized as a flowchart shown in Fig. 6 while results from the training process can be shown in Fig. 7.

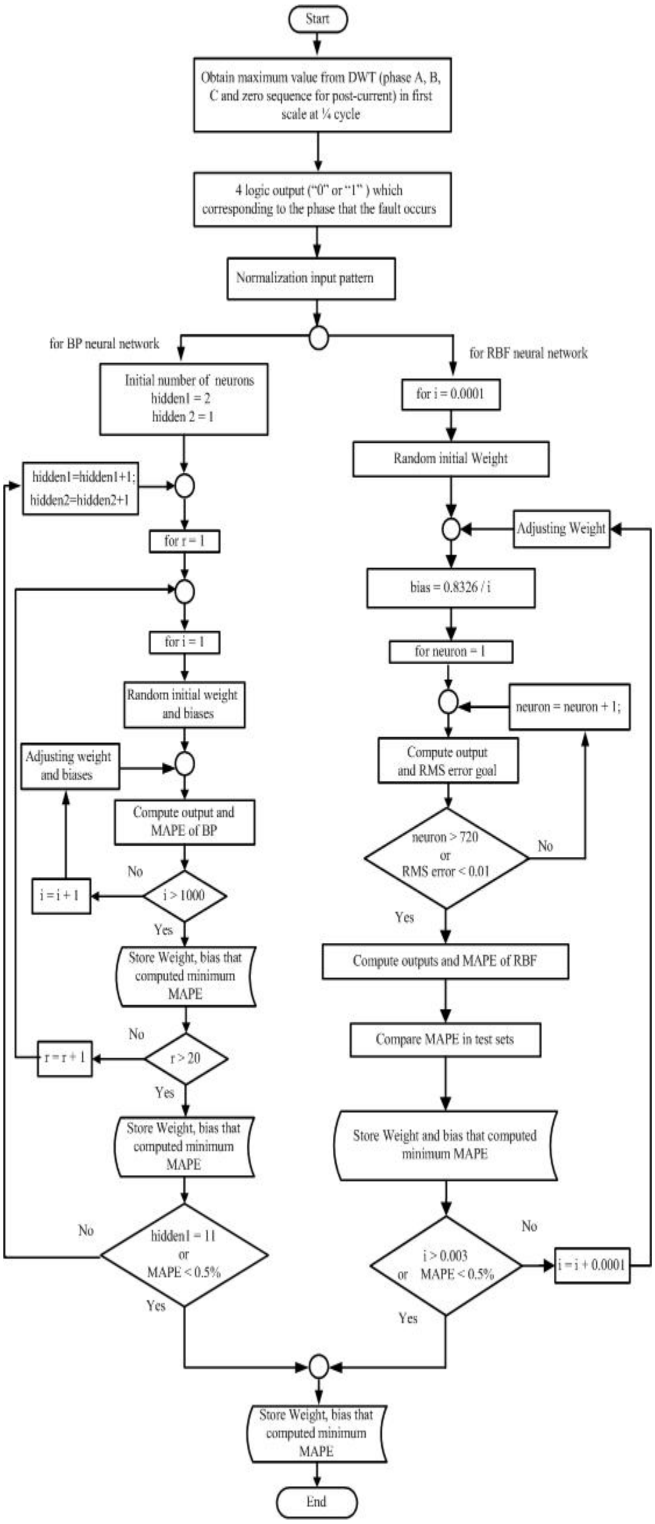

Fig. 6. Flowchart for the training process.

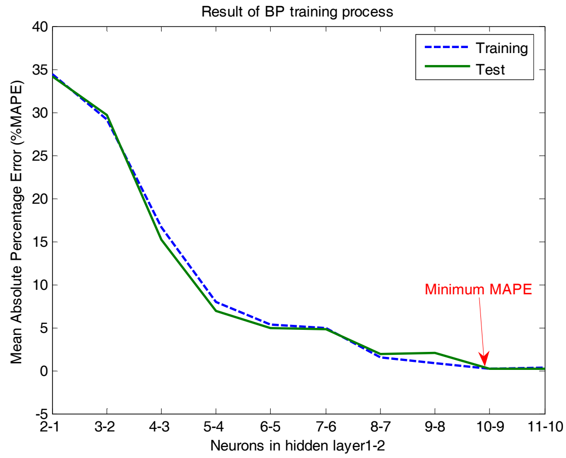

Fig. 7. Result of BP training process.

B. *Radial Basis Function Neural Networks*

A structure of a RBF neural network consists of three layers which are an input layer, a hidden radial basis layer and an output linear layer [11]. Each layer is connected with weight and bias while radial basis function and linear function are activation function in hidden radial basis layer and output linear layer respectively. Generally, RBF neural network have only hidden radial basis layer for which the combination function is based on the Euclidean distance between the input vector and the weight vector. The only fundamental difference is the way in which hidden units combine value coming from preceding layers in the network—BP neural network use inner products, while RBF neural network use Euclidean distance. In addition, the number of neurons in radial basis layer is always equal to the number of training sets.

A training process of RBF [11] involves two stages as follows :

1. Input values are propagated to each neurons in the first layer. The radial basis layer computes distances from the input vector to weight vector, and produces output in radial basis layer as in Equation 5.

$$\varphi(p) = \exp\left(-\frac{\left\|p - IW_{1,1}\right\|^2}{\sigma_j^2}\right) \tag{5}$$

where,

p is the input pattern vector

$IW_{1,1}$ is the center vector of hidden radial basis layer

σ is the spread constant for hidden radial basis layer which corresponds to bias value ($b = \frac{0.8326}{Spread}$)

$\varphi(p)$ is the output of radial basis layer

2. Each neuron in the linear layer receives data from the hidden radial basis layer which are locally responsive to input stimulus, and then calculating responses from input pattern vector with weight vector and bias in the linear layer. Finally, a linear activation function on the linear layer compute output of RBF as in Equation 6 [11].

$$o/p_{ANN} = f^3\left(LW_{2,1} * \varphi(p) + b^4\right) \tag{6}$$

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where, b^4 is the bias in the linear layer
$LW_{2,1}$ is the weight vector between hidden radial basis layer and linear layer

During training process [11], RBF neural network begin with the random initial weight and bias in all layers. The number of neurons in hidden radial basis layer is equal to the number of iteration. RMS error goal is determined as 0.01 in each iteration while increasing spread in hidden radial basis layer which corresponds to bias value ($b = \frac{0.8326}{Spread}$) from 0.0001 until 0.003. The step of increase spread is at 0.001 in order to computes the minimum value of MAPE. This procedure is repeated until the number of spread is reached or the MAPE of test sets is less than 0.5% then stop training process. The training process can be summarized as a flowchart shown in Fig. 6 while results from the training process can be shown in Fig. 8.

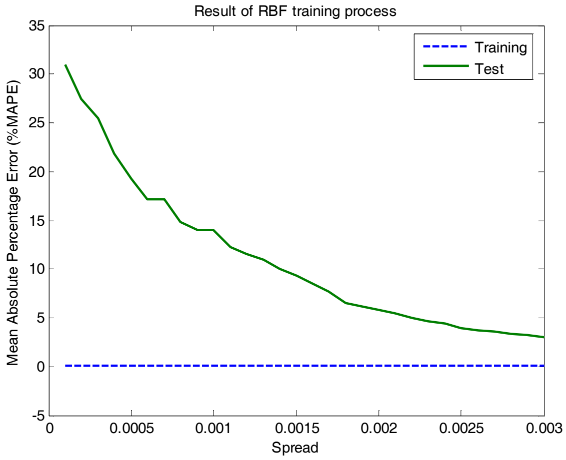

Fig. 8. Result of RBF training process.

C. Results.

After the training process, the results obtained from the decision algorithm proposed in this paper are shown in Table 2. 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 Fig. 9-10. In addition, the results obtained from the comparison of average accuracy among decision algorithm using ANNs and decision algorithm using the comparison of the coefficients DWT which developed by Markming et al [6] are shown in Table 3. 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 [6].

Table 2 Comparison results of training process

Information for comparison	BP	RBF
Number of neurons input	8	8
Number of neurons in hidden 1	10	611
Number of neurons in hidden 2	9	-
Spread	-	0.003
Number of neurons output	4	4
Number of Training set	728	728
Iterations	20000	611
Training time (minute)	161	50

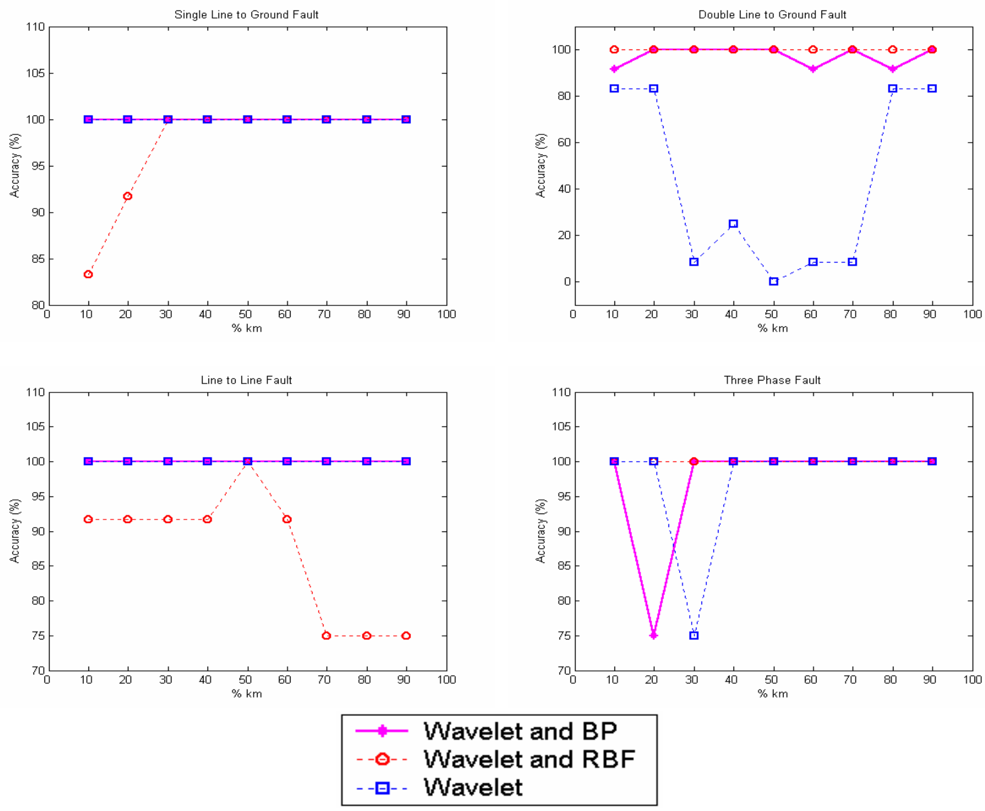

Fig 9. Comparison of average accuracy for fault types at various lengths of the transmission lines that fault occur

Fig. 10. Comparison of average accuracy for fault types at various types of faults

Table 3 Percentage average accuracy for fault types

Classify of the fault types	Number of Case Studies	Fault Classification		
		Wavelet and BP	Wavelet and RBF	Trail and error method [6]
Single line to ground fault	108	100.00%	97.22%	100.00%
Double line to ground fault	108	97.22%	100.00%	42.59%
Line to line fault	108	100.00%	87.04%	100.00%
Three phase fault	36	97.22%	100.00%	97.22%
Average		98.89%	96.85%	83.33%

V. Conclusion

A technique using discrete wavelet transform in combination with artificial neural networks in order to classify of fault type on single circuit transmission lines has been proposed. Daubechies4 (db4) is employed as mother wavelet in order to decompose high frequency components from fault signals. Coefficients of positive sequence current signals are calculated and it is employed in fault detection decision algorithm which can detect fault in scale 1 from DWT with the accuracy of 100%. The maximum values from the first scale at ¼ cycle of phase A, B, C and zero sequence of post-fault current signals obtained by the discrete wavelet transforms have been used as an input for the training process of an artificial neural network in a decision algorithm. In addition, Back-Propagation neural network is also compared with RBF neural network in this paper and the comparison between an average accuracy in fault classifications obtained from the artificial neural network algorithm is shown in Table 2 and 3. Various case studies have been studied including the variation of fault inception angles and fault types. The result is shown that an average accuracy values obtained from RBF is able to give satisfactory results with less training time compared with BP neural networks. The further work will be the investigation of the RBF for the instance loop circuits or complicated system.

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