Discrete Wavelet Transform and Back-propagation Neural Networks Algorithm for Fault Classification in Underground Cable

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***Abstract*—This paper proposes a new technique using discrete wavelet transform (DWT) and back-propagation neural network (BPNN) for fault classifications on underground cable. Simulations and the training process for the back-propagation 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. Various cases studies based on Thailand electricity distribution underground systems have been investigated so that the algorithm can be implemented. The results are shown that an average accuracy values obtained from BPNN can indicate the fault classification with satisfactory accuracy, and will be very useful in the development of a power system protection scheme.**

***Index Terms*—Wavelet Transform, Fault Classification, Underground Cable, Neural Network, ATP/EMTP.**

I. Introduction

In previous decade, several decision algorithms for fault classification and identification have been developed, then to be employed in the protective relays. However, most research works have only considered the fault diagnosis for overhead transmission systems [1-11], but not for underground distribution system. In a few years ago, the application of wavelet transform and other intelligent technologies are developed for the fault diagnosis in underground cable.

The idea of application of wavelet transform to fault diagnosis is not new, and there is most research papers related to this idea [12-13]. In previous research works [13], 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 it may not be adequate to complete characterization. In recent years, the artificial intelligent has been rapidly developed and neural networks have been successfully applied in several fields [14-17]. Back-propagation neural network (BPNN) is the most well known and widely applied today, because it can solve almost all types of problems. Normally, the algorithm uses BPNN to indicate the proper decision. It is interesting to investigate an appropriate neural network, and implement it in newly-developed protection systems.

Hence, the objective of this paper is to consider studies of the BPNN for the decision algorithm used to classify fault type in underground cable distribution system. The simulations, analysis and diagnosis are performed using ATP/EMTP and MATLAB on a PC Pentium IV 2.2 GHz 3GB. It is noted that the DWT is employed in extracting the high frequency component contained in the fault currents, and the coefficients of the first scale from the DWT that can detect fault are investigated. The construction of the decision algorithm is detailed and implemented with various case studies based on Thailand electricity underground distribution systems.

II. Simulation

Artificial neural networks (ANN) 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 require fault signal samples from simulations to training and test processes. The ATP/EMTP [18] is employed to simulate fault signals, at a sampling rate of 200 kHz. The system employed in case studies is chosen based on the underground distribution system as illustrated in Figure 1. In addition, a cross-sectional view of a cable is shown in Figure 2. To avoid complexity, the fault resistance is assumed to be 10Ω. Fault patterns in the simulations are performed with various changes of system parameters as follows:

- Fault types are single line to ground, double lines to ground, line to line and three-phase fault.
- Fault locations are from 1 km to 5 km (each step = 1 km) of the underground cable length measured from the sending end
- Fault inception angles on the phase A voltage waveform were varied from 0° to 150° with a step of 30°

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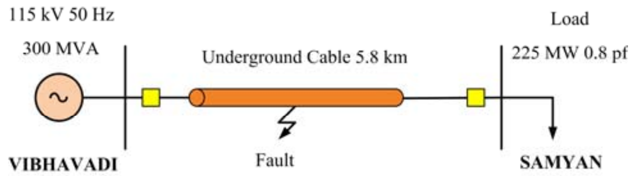

Figure 1. The system used in simulation studies [19].

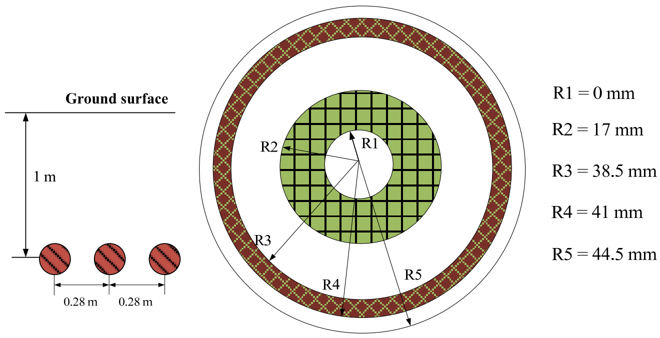

Figure 2. The configuration of cable in simulation studies

The example of ATP/EMTP simulated fault signals is illustrated in Figure 3. This is a fault occurring in phase A to ground at 1 km measured from the sending bus as depicted in Figure 1. The fault signals generated using ATP/EMTP are interfaced to MATLAB for the fault detection algorithm.

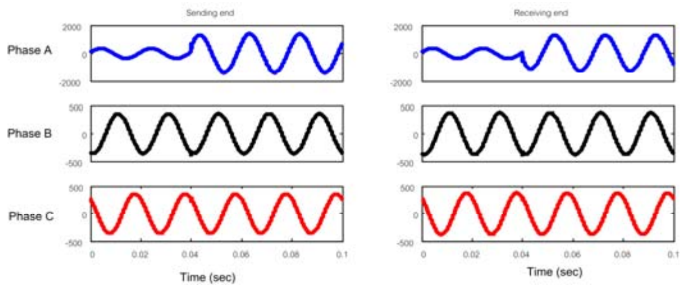

Figure 3. Example of ATP/EMTP simulated fault signals for AG fault at sending end.

III. Fault Detection Algorithm

Fault detection decision algorithm [13] is processed using positive sequence current signal. The Clark's transformation matrix is employed for calculating the positive sequence and zero sequence of currents. The mother wavelet daubechies4 (db4) [4, 6-8, 13, 20] is employed to decompose high frequency components from the positive sequence current signals. Coefficients obtained using DWT of signals are squared so that the abrupt change in the spectra can be clearly found, and it is obviously 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 Figure 4. The fault detection decision algorithm [4, 6, 13] has been proposed that if coefficients of any scales are changed around five times before an occurrence of the faults, there are faults occurring on transmission lines or underground cables.

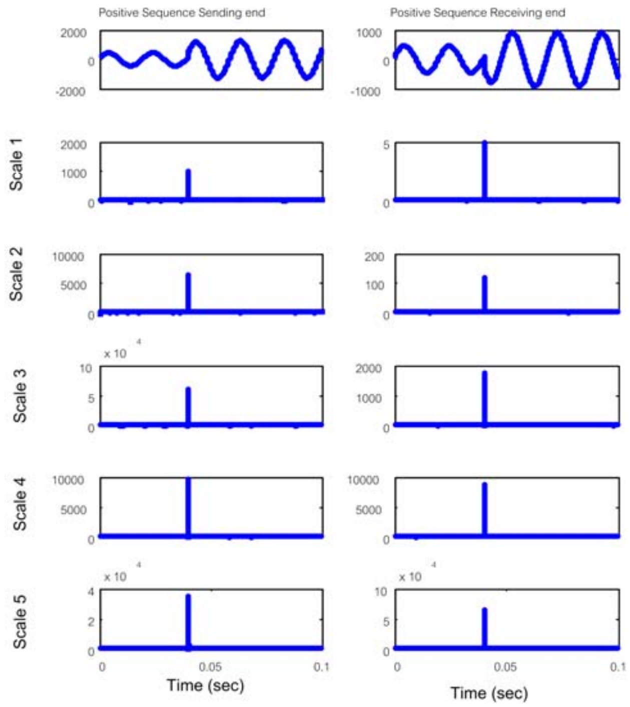

Figure 4. Wavelet transform from scale 1 to 5 for the positive sequence of current signal shown in Figure 3.

From Figure 4, the coefficients in all scale of the wavelet transform are clearly changed then it presumes that these signals are fault 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. Moreover, and the coefficients in scale 1 from DWT are used later in training processes for the neural networks.

IV. Decision Algorithm and Result

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 BPNN. A training process is performed using neural network toolboxes in MATLAB [21]. Before the training process, input data sets are normalized and divided into 300 sets for training and 150 sets for tests. A structure of the BPNN 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 Figure 5. The output variables of the BPNN are designated as value range from 1 to 10 which corresponding to various types of fault as shown in Table 1.

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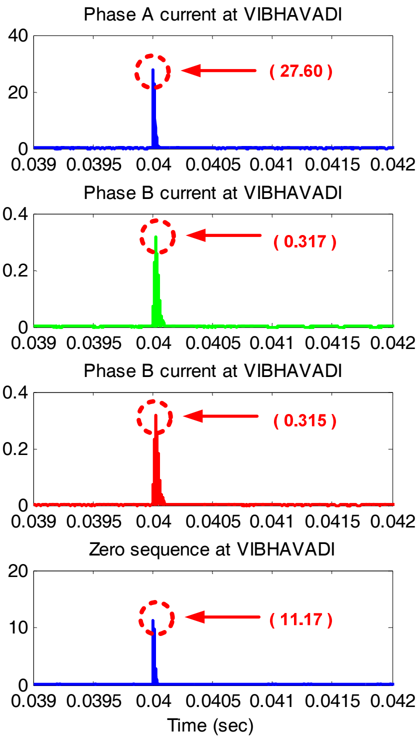

Figure 5. Magnitude in scale 1 for post-fault all phase of current signal shown in Figure 3.

Table 1 Output of ANNs for classifying the fault types

Output of BPNN	Classification of fault type	Types of fault
1	Phase A to ground fault	AG
2	Phase B to ground fault	BG
3	Phase C to ground fault	CG
4	Phase A,B to ground fault	ABG
5	Phase B,C to ground fault	CAG
6	Phase C,A to ground fault	BCG
7	Three phase fault	ABC
8	Phase A to phase B fault	AB
9	Phase C to phase A fault	CA
10	Phase B to phase C fault	BC

In this paper, BPNN consists of three layer of neurons [22] (Input, two-hidden, output) interconnected by weights as shown in Figure 6. 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 BPNN can be divided into three parts as follows [21, 22]:

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 1 and 2.

$$a^2 = f^2\left(lw^{2,1} * f^1\left(iw^{1,1} * p + b^1\right) + b^2\right), \quad (1)$$

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

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 to try to match between the calculated outputs and the target outputs. Mean absolute percentage error (MAPE) as an index for efficiency determination of the BPNN is computed by using Equation 3.

$$MAPE = \frac{1}{n} * \sum_{i=1}^{n} \left| \frac{o/p_{ANNi} - o/p_{TARGETi}}{o/p_{TARGETi}} \right| * 100\% \quad (3)$$

where, n is the number of test sets.

During training process [22], 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 Figure 7 while results from the training process can be shown in Table 2 and Figure 8.

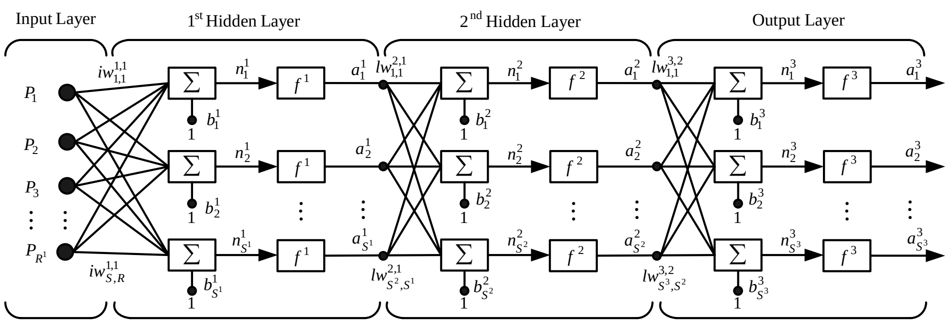

Figure 6 Back-propagation with two hidden layers

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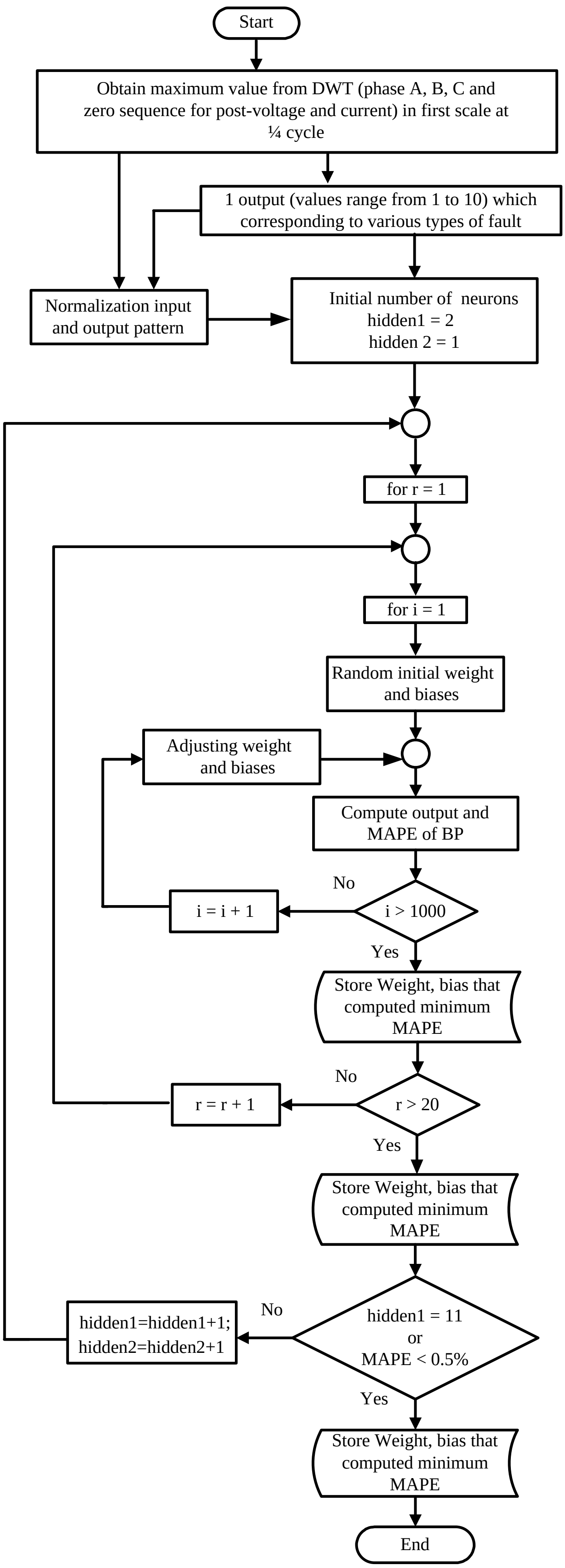

Figure 7. Flowchart for the training process.

After the training process, the decision algorithm is employed in order to classify the fault in the underground distribution line. Case studies are varied so that the decision algorithm capability can be verified. The total numbers of the case studies are 150. Various case studies are performed with various types of faults including the variation of fault inception angles and locations in underground cable. In addition, the results obtained from the comparison of average accuracy between decision algorithm using BPNN and decision algorithm using the comparison of the coefficients DWT, developed by Apisit et al [13] are shown in Table 3. The results are 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 coefficient comparison technique developed by Apisit et al [13].

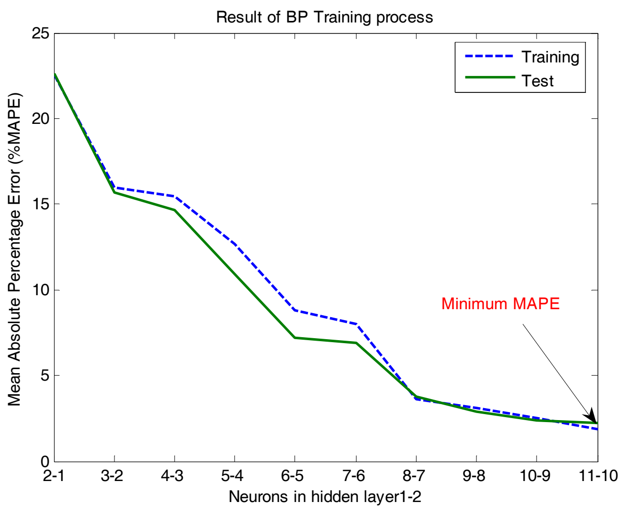

Figure 8. Result of BP training process.

V. Conclusion

A technique using discrete wavelet transform in combination with BPNN in order to classify of fault type in underground distribution system has been proposed. Daubechies4 (db4) is employed as mother wavelet in order to decompose high frequency components from fault signals. 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 the BPNN in a decision algorithm. Various case studies have been studied including the variation of fault inception angles and fault types. It is shown that combination of wavelet transform and BP neural networks is a powerful tool owing to its satisfactory results as shown in Table 3. The further work will be the improvement of the algorithm so that locations of fault along the structure of distribution system can be identified.

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TABLE 2 RESULTS AND MAPE OF BPNN

Number neuron in hidden 1-2	2-1	3-2	4-3	5-6	6-5	7-6	8-7	9-8	10-9	11-10
MAPE of Training	22.5633	15.9789	15.442	12.6769	8.8342	7.9732	3.641	3.1025	2.5039	1.8509
MAPE of Test	22.6091	15.683	14.6266	10.9441	7.2112	6.8812	3.7931	2.8659	2.3646	2.1981
Training time (minute)	1.24	1.3	1.47	2.07	2.28	3.12	4.06	5.08	6.21	8.24

Table 3 Percentage average accuracy for fault types

Classification of the fault types	Number of Case Studies	Fault Classification	
		Wavelet and BP	coefficient comparison technique [13]
Single line to ground fault	45	100.00%	80.00%
Double line to ground fault	45	100.00%	80.00%
Line to line fault	45	100.00%	100.00%
Three phase fault	15	93.33%	100.00%
Average		98.33%	90.00%

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