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SELECTION OF PROPER ARTIFICIAL NEURAL NETWORKS FOR FAULT CLASSIFICATION ON SINGLE CIRCUIT TRANSMISSION LINE

Sulee Bunjongjit and Atthapol Ngaopitakkul

Faculty of Engineering
King Mongkut's Institute of Technology Ladkrabang
Chalongkrung Rd., Ladkrabang, Bangkok 10520, Thailand
knatthap@kmitl.ac.th

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Abstract. *This paper proposes a new technique using discrete wavelet transform (DWT) and artificial neural networks for fault classification on single circuit transmission line. Simulation and the training process for the artificial neural networks are performed using ATP/EMTP and MATLAB respectively. The mother wavelet daubechies4 (db4) is employed to decompose high frequency component from these current signals. Positive sequence current signals are employed in faults detection decision algorithm. The variations of first scale high frequency component detecting faults are employed as an input for the training process. Back-propagation (BP) neural network, Radial basis function (RBF) neural network and Probabilistic neural network (PNN) are compared in this paper. The results are shown that average accuracy values obtained from PNN give satisfactory results with less training time.*
Keywords: Wavelet transform, Neural networks, Transmission line, Fault classification

1. 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. The method of symmetrical components is based on fault analysis for over 60 years in various protective relay applications. During 1980s, the several techniques used to detect and classify the faults on transmission lines are discussed, such as the variation of the voltage and current of the three phases [1], the ratio of the change in the magnitude of current to threshold value [2] and a statistical method based on a discriminate value [3].

During 1990s, there were widespread applications of artificial neural networks in power systems. Artificial intelligence (AI) has been reported in the literature for fault classification [4-8]. A fault detection and classification scheme based on genetic algorithm based neural networks is presented in [5]. A new approach to real-time fault detection and classification in power transmission systems by using fuzzy-neuro techniques is presented in [6]. In [7], this paper reports studies on five different neural network models applied to classification of faults on complex transmission lines. However, there are still problems associated with hardware such as the lack of good analog memories and the limited number of interconnections. By the end of the 1990s, the traditional method of signal analysis was carried out based on Fourier transform, but the fault signals are non-stationary transient, so the signal analysis methods with Fourier transform are not quite efficient. The development in the algorithm for detecting the faults on the transmission lines has been progressed and resulted in transient based techniques [9]. The transient based protection has been found that the wavelet transform is capable of investigating the transient signals generated in power system [10]. The wavelet transform was initially proposed in the literature for fault classification by O. A. S. Youssef [11]. The wavelet transform concept and its value in classification techniques and feature detection schemes are presented in [11]. In several research papers, the fault classification can be obtained by employing trial and error method [12-15]. In previous research works [13], by considering the pattern of the spectra, the comparison of the coefficients from first scale that can detect faults is considered. The division algorithm between the maximum coefficients of DWT at 1/4 cycle of phase A, B and 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 faults can be analysed. Although the wavelet transform is very effective in detecting transient signals generated by the faults, the wavelet transform may not be adequate to complete characterization.

In previous decade, several decision algorithms [16-25] for fault classification and identification have been developed, then to be employed in the protective relays. O. A. S. Youssef et al. [16] presented a new approach of real-time fault classification in power transmission systems using fuzzy-logic-based multi-criteria approach. Only the three line currents are utilized to detect fault types such as LG, LL and LLG, and then to define the faulty line. DWT integrated with a fuzzy logic system [17] is designed for fault classification of a transmission line. The approach exploits information obtained from the wavelet decomposition of current signals for faulty phase selection and section identification. In [18], an approach for line protection based on fault characteristics extraction was presented. Analysis of the spectral energy of the phase voltage signals for different frequency bands enables faults to be detected and classified. A novel method for transmission-line fault detection and classification using oscillographic data is presented in [19]. An artificial neural network classifies the fault from the voltage and current waveforms pattern recognition in the time domain.

Nowadays, the neural networks have been rapidly developed and successfully applied in several fields [26-31]. Back-propagation neural network is a kind of neural networks, which is widely applied today owing to its effectiveness to solve almost all types of problems. However, in practice, back-propagation neural network is partly limited by the slow training performance. It should improve this drawback of back-propagation neural network otherwise the other types of neural networks should be developed instead. Probabilistic neural network (PNN) has been successfully used to solve a diverse group of classification problems. Even though the PNN has not been yet fully evaluated compared with back-propagation neural network, the PNN approach offers major advantages, such as rapid training and added or deleted data from training set without lengthy retaining. Besides, Radial basis function (RBF) neural network is the most commonly-used type of feed-forward network as well as the back-propagation neural network. As a result, the objective of this paper is to consider studies of the artificial neural networks for classification of faults on single circuit transmission line. RBF neural network and PNN are selected in order to be compared with back-propagation neural network, and the results obtained from the decision algorithm are investigated in this paper. The simulations, analysis and diagnosis are performed using ATP/EMTP and MATLAB on a PC Pentium IV 2.4 GHz 512 MB. The discrete wavelet transform is employed in extracting the high frequency component contained in the fault current. The coefficients of the first scale from the DWT are investigated, and then are used as an input for a training process on the neural networks. The construction of the decision algorithm is detailed and implemented with various case studies based on Thailand electricity transmission systems.

2. **Power System Simulation Using EMTP.** Artificial neural networks are an attempt to simulate the human brain's nonlinear and parallel processing capability for many 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 process and test process. The ATP/EMTP [32] is used to simulate fault signals at a sampling rate of 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 illustrated in Figure 1. Fault patterns in the simulations are performed with various changes of system parameters as follows:

- Fault types under consideration are 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 is equal to 10 Ω.

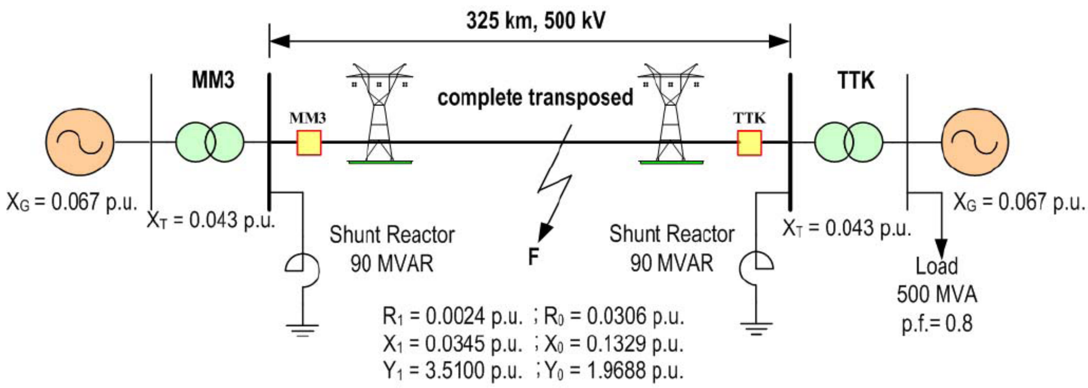
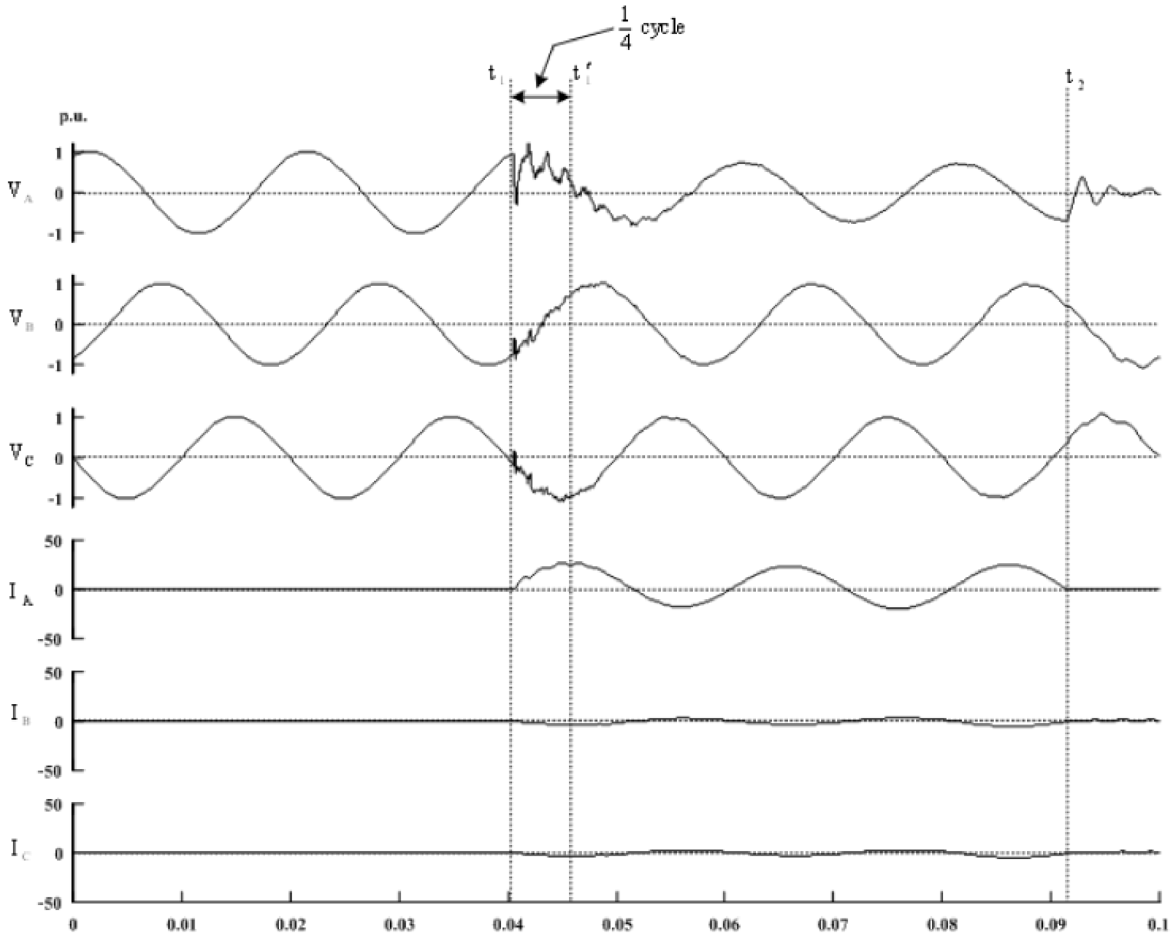


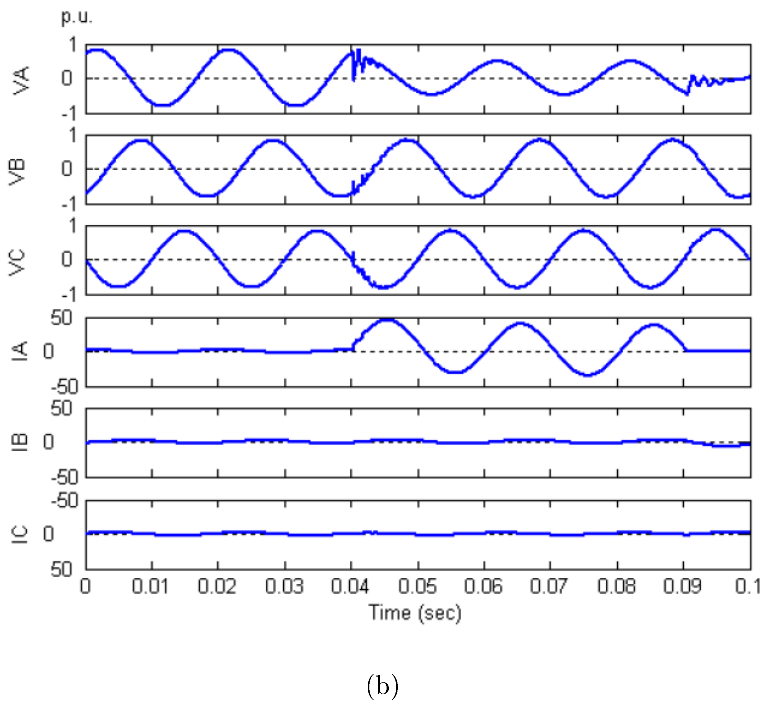
FIGURE 1. The system used in fault simulations [13,31,33]

The examples of original and ATP/EMTP simulated fault signals for phase A to ground fault (AG) in each phase at the sending end (MM3) of the transmission line, are illustrated in Figures 2(a) and 2(b), respectively. This is a fault occurring with phase A to ground fault (AG) at the length of 35% measured from the bus MM3 as shown in Figure 1. The similarity between the two waveforms can be seen by visually inspecting the original and simulated fault signals. The fault signals generated using ATP/EMTP are interfaced to the MATLAB/Simulink for a construction of fault diagnosis process.

The Clark's transformation matrix is employed for calculating the positive sequence and zero sequence of currents. Fault detection decision algorithm is processed using positive sequence current signal. The mother wavelet daubechies4 (db4) [13,25,30,34] is employed to decompose high frequency components from the signals. After applying the Wavelet transform to the positive sequence currents, coefficients obtained using DWT of signals are squared. The comparison of the coefficients from each scale is under investigation. The result is clearly seen that when fault occurs, the coefficients of high frequency components have a sudden change compared with those before an occurrence of the faults as illustrated in Figure 3. This abrupt change is used as an index for the occurrence of faults as shown in Table 1.



(a)



(b)

Figure 2. (a) Example of original fault signals for phase A to ground fault; (b) example of ATP/EMTP simulated fault signals for phase A to ground fault

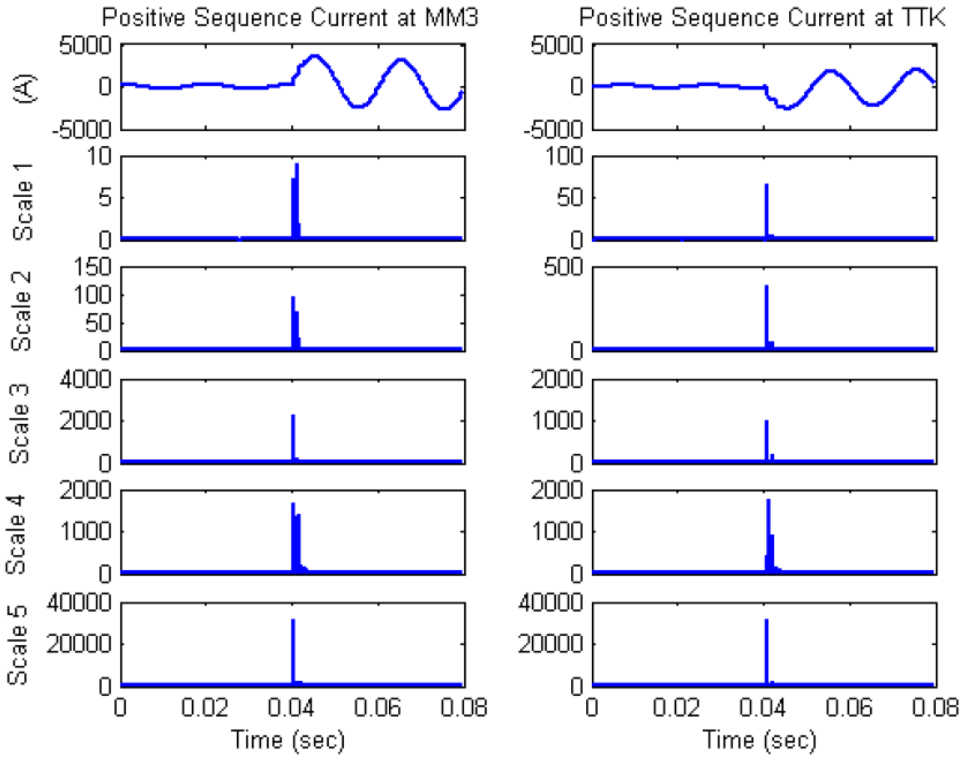


Figure 3. Wavelet transform from scale 1 to 5 for the positive sequence of current signals shown in Figure 2(b)

Table 1. Results for fault detection from signals shown in Figure 3

Wavelet scale	Positive Sequence Current (MM3)		Positive Sequence Current (TTK)		Result
	Max (pre)	Max (post)	Max (pre)	Max (post)	
1	0.0020	9.0323	0.0094	66.2263	Fault
2	0.0004	94.5754	0.0021	387.3067	Fault
3	0.0043	2310.6	0.0234	994.7926	Fault
4	0.0236	1662.9	0.1485	1755.1	Fault
5	0.2306	31844	0.7545	31811	Fault

Table 2. Results for fault detection from signal shown in Figure 4

Wavelet scale	Positive Sequence Current (MM3)		Positive Sequence Current (TTK)		Result
	Max (pre)	Max (post)	Max (pre)	Max (post)	
1	0.00003	0.00001	0.0001	0.00002	Normal
2	0.00005	0.00005	0.0001	0.00004	Normal
3	0.0001	0.0001	0.0003	0.0002	Normal
4	0.0015	0.0014	0.0037	0.0033	Normal
5	0.023	0.0226	0.0573	0.0555	Normal

From Figure 4, the coefficient detail (cD1) in each scale of the wavelet transform does not obviously change, so the result obtained from fault detection algorithm can presume the normal condition of these signals as shown in Table 2. By performing many simulations [13,25,31], the coefficient in scale 1 from DWT seems enough to indicate the fault inception

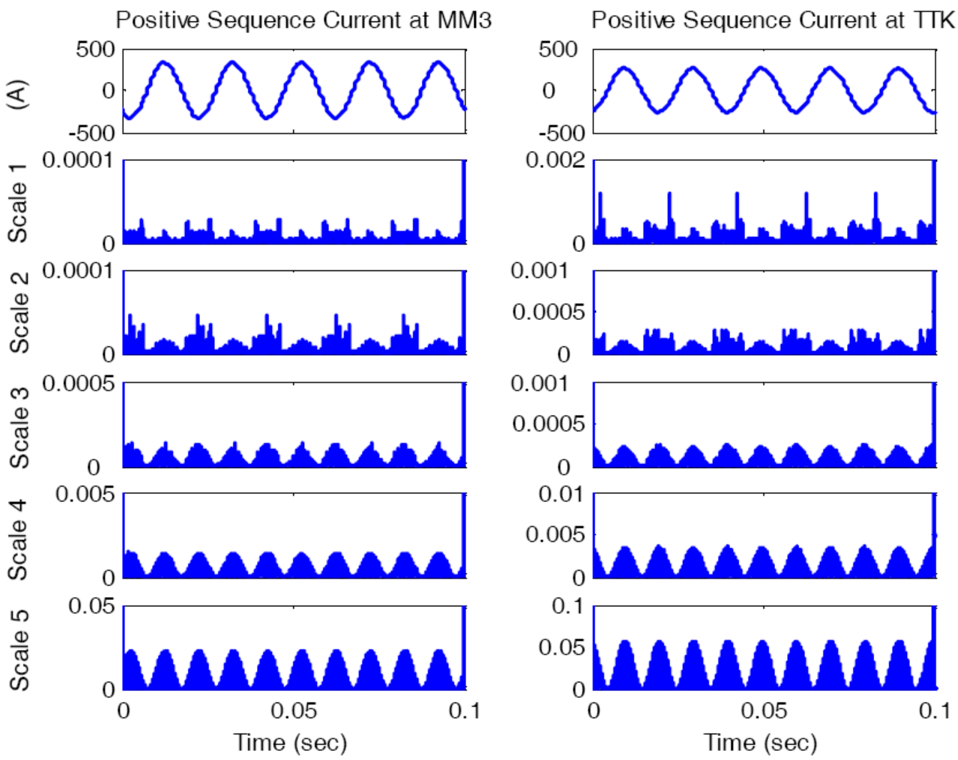


FIGURE 4. Wavelet transform from scale 1 to 5 for the positive sequence of current signal in normal condition

on the single circuit transmission line. Consequently, fault detection algorithm is assumed that if coefficients of any scale are changed around five times before an occurrence of the faults, there are faults occurring on transmission line and the coefficients in first scale that can detect fault is investigated.

3. Neural Network Decision Algorithm and Results.

From the fault detection algorithm, DWT is 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 MATLAB [35]. 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 inputs and 1 neuron outputs. The input patterns are maximum coefficients of DWT at 1/4 cycle of phase A, B and C, and zero sequence for post-fault current waveforms as illustrated in Figure 5. The output variables of the artificial neural networks are designated as value range from 1 to 10, which corresponds to various types of fault as shown in Table 3.

3.1. Back-propagation neural networks.

In this paper, back-propagation neural network consists of three layers of neurons (input, two-hidden and output) interconnected by weights and bias as shown in Figure 6. The inputs are fully connected to the first hidden layer, each hidden layer is fully connected to the next layer and the last hidden layer is fully connected to the output layer. In addition, hyperbolic tangent sigmoid functions are used as an activation function in all hidden layers whereas linear function is used as an activation function in output layers.

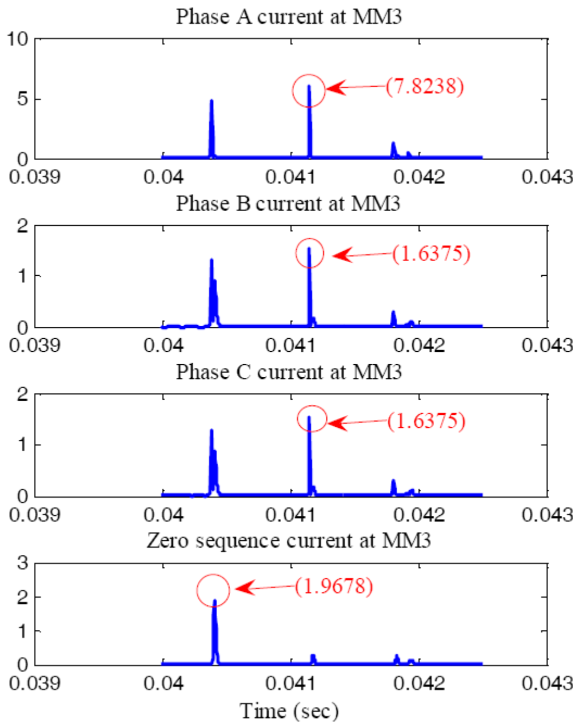


FIGURE 5. Magnitude in scale 1 for post-fault all phase of current signal shown in Figure 2

TABLE 3. Output of ANNs for classifying the fault types

Output of ANNs	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 and B to ground fault	ABG
5	Phase B and C to ground fault	CAG
6	Phase C and 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

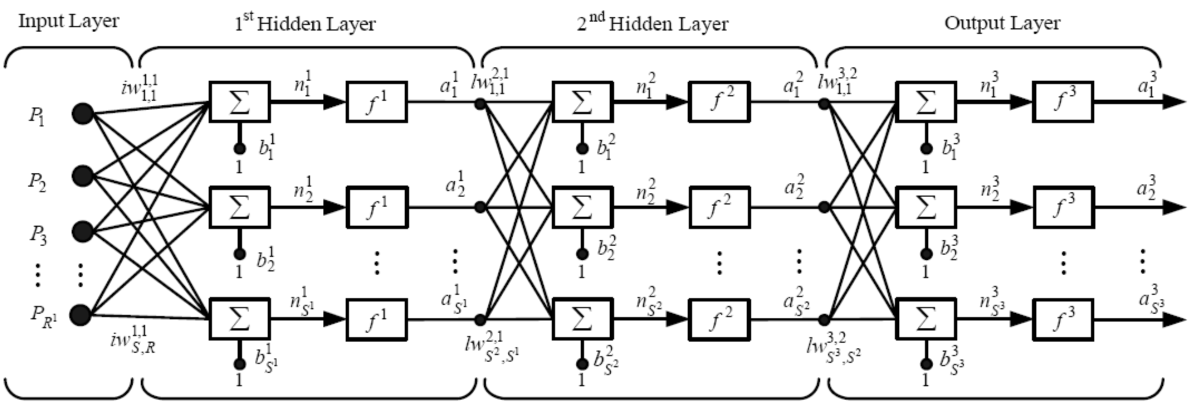


FIGURE 6. Back propagation with two hidden layers [35]

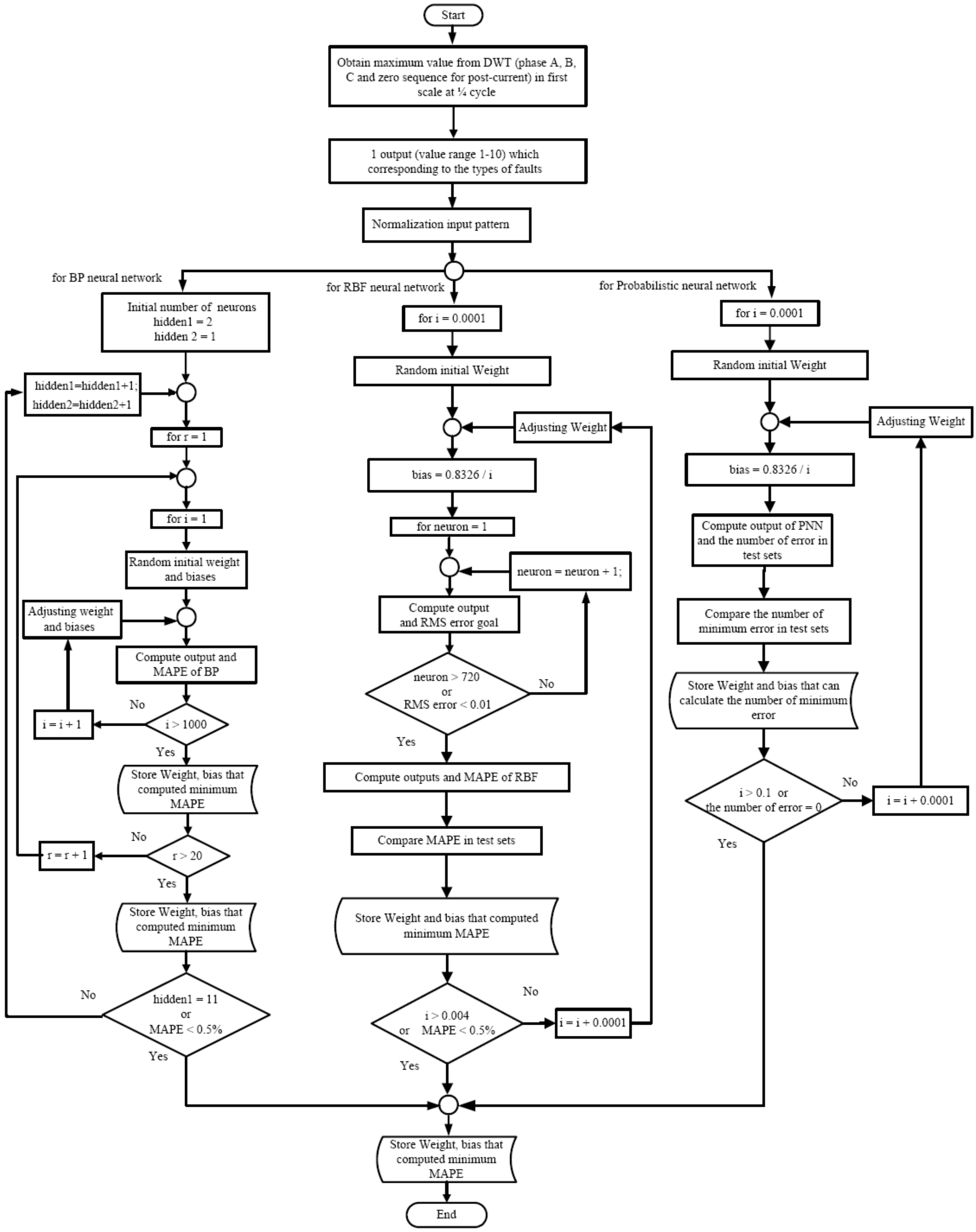


Figure 7. Flowchart for the training process

During training process [30,31], the weights and biases are adjusted, and there are 20,000 iterations taken to compute the optimum value of MAPE as expressed in Equation (1). 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 set is less than 0.5%. The training process can be summarized as a flowchart illustrated in Figure 7 while results from the training process can be shown in Table 4.

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

where n is the number of test sets.

TABLE 4. Comparison results of training process

Information for comparison	BP	RBF	PNN
Number of neurons input	4	4	4
Number of neurons in hidden 1	11	611	611
Number of neurons in hidden 2	10	–	–
Spread	–	0.004	0.0022
Number of neurons output	1	1	1
Number of Training set	720	720	720
Number of Test set	360	360	360
Iterations	20000	611	611
Total time of training process (minute)	20	50	1

3.2. **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 as illustrated in Figure 8. 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 has 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 uses inner products, whereas RBF neural network uses Euclidean distance. In addition, the number of neurons in radial basis layer is always equal to the number of training sets.

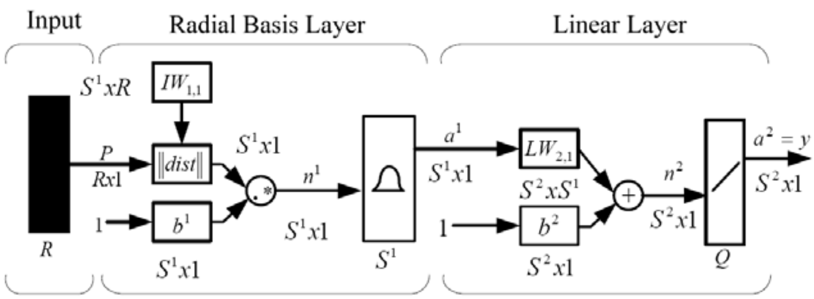


FIGURE 8. Radial basis function neural networks [35]

During training process [31,35], RBF neural network begins 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 iterations. RMS error goal is determined as 0.01 in each iteration while increasing spread in hidden radial basis layer, which corresponds to bias value $\left(b = \frac{0.8326}{Spread}\right)$ from 0.0001 to 0.004. The appropriate step of increasing spread is 0.001

in order to compute the minimum value of MAPE. This procedure is repeated until the number of spread is reached, or the MAPE of test set is less than 0.5% then stop training process. The training process can be summarized as a flowchart illustrated in Figure 7 while results from the training process can be illustrated in Table 4.

3.3. **Probabilistic neural networks.** Probabilistic neural network (PNN) is developed by Donald Specht, to perform pattern classification using Gaussian potential functions and Bayes decision theory [36]. The PNN consists of three layers, which are an input layer, a hidden radial basis layer and a competitive layer as illustrated in Figure 9. Each layer is interconnected by weights. Radial basis function and competitive function are activation function in hidden radial basis layer and competitive layer respectively. Moreover, the number of neurons in radial basis layer is always equal to the number of training sets similarly to RBF neural network.

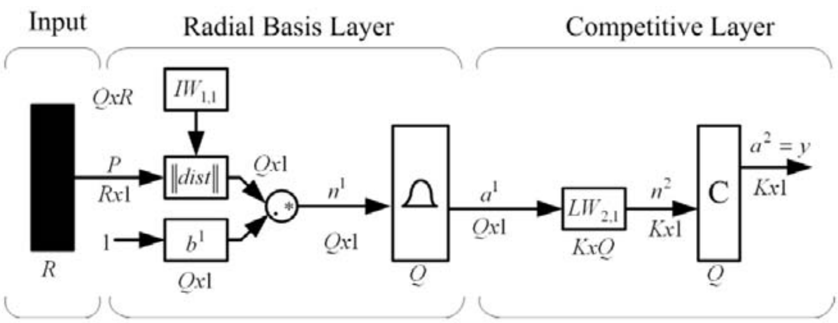


FIGURE 9. Probabilistic neural network [35,37]

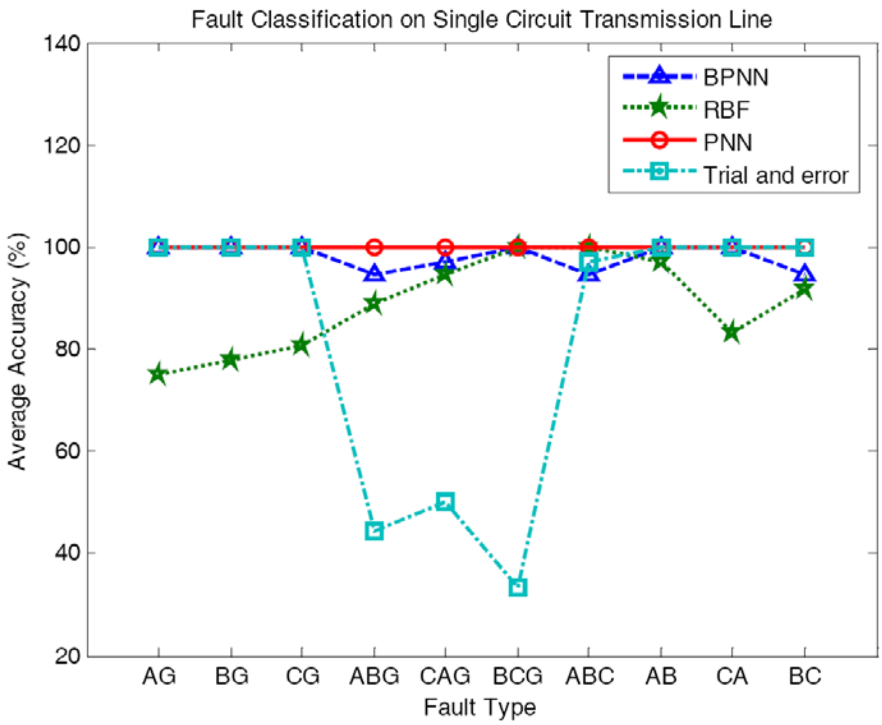


FIGURE 10. Comparison of average accuracy of fault classification for various types of faults

During the training process [35,37], PNN begins with the random initial weight and increasing spread in the radial basis layer, which corresponds to bias value $\left(b = \dfrac{0.8326}{Spread}\right)$ from 0.0001 to 0.1. The step of increase is 0.0001 to compute the number of minimum error. This procedure is repeated until the maximum number of spread is reached, or the number of minimum error is equal to zero then stop training. The training process can be summarized as a flowchart illustrated in Figure 7 while results from the training process are illustrated in Table 4.

3.4. **Results.** After the training process, the results obtained from the proposed decision algorithm are shown in Table 4. Case studies are varied so that the decision algorithm capability can be verified. The total numbers of the case studies are 360. In addition, various case studies are performed with various types of faults on the single circuit transmission line including the variation of fault inception angles and locations at each transmission line as shown in Figure 10 and Table 5. Table 5 shows the comparison of average accuracy between decision algorithm using ANNs and the comparison of the coefficients

TABLE 5. Comparison of average accuracy of fault classification for various lengths of the transmission lines that fault occurs

In case of		10	20	30	40	50	60	70	80	90	Accuracy
SLG	BPNN	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
	RBF	8.33%	58.33%	41.67%	91.67%	100%	100%	100%	100%	100%	77.78%
	PNN	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
	Trial and error [13]	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
DLG	BPNN	100%	100%	100%	100%	91.67%	100%	91.67%	91.67%	100%	97.22%
	RBF	75.00%	75.00%	100%	100%	100%	100%	100%	100%	100%	94.44%
	PNN	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
	Trial and error [13]	83.33%	83.33%	8.33%	25.00%	0.00%	8.33%	8.33%	83.33%	83.33%	42.59%
L-L	BPNN	91.67%	100%	100%	100%	100%	100%	91.67%	100%	100%	98.15%
	RBF	58.33%	91.67%	75.00%	100%	91.67%	100%	100%	100%	100%	90.74%
	PNN	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
	Trial and error [13]	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
3-P	BPNN	100%	100%	100%	100%	100%	100%	100%	75.00%	75.00%	94.44%
	RBF	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
	PNN	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
	Trial and error [13]	100%	100%	75.00%	100%	100%	100%	100%	100%	100%	97.22%

TABLE 6. Percentage accuracy of test set for classification of fault type

Classification of the fault types	Number of case studies	Wavelet and artificial neural network			Trial and error method [13]
		BP	RBF	PNN	
Single line to ground fault	108	100.00%	77.78%	100.00%	100.00%
Double line to ground fault	108	96.30%	94.44%	100.00%	42.59%
Line to line fault	108	98.15%	90.74%	100.00%	100.00%
Three phase fault	36	94.44%	100.00%	100.00%	97.22%
Average		98.06%	88.89%	100.00%	83.33%

DWT, which is developed by Markming et al. [13] at various lengths of the transmission lines that fault occurs. The comparison between an average accuracy in fault classification obtained from the ANNs algorithm proposed in this paper and that of the former wavelet algorithm [13] is shown in Table 6. The result is shown that the accuracy of fault classification from the proposed decision algorithm in this paper is highly satisfactory.

From Tables 6, the result can be seen that the PNN decision algorithm can give a better performance in predicting the fault types, so PNN is selected in the decision algorithm. This is an improvement of the fault classification which is detected using the trial and error method developed by Markming et al. [13]. In addition, the decision algorithms provide good responses of output values to new input data (different fault resistances) without training as shown in Table 7.

Table 7. Results of different fault types for different fault resistances (fault at 30% of transmission lines and at inception angle of 90°)

Fault type	**Real Location (km)**	**Fault Resistance (Ω)**	**Fault Type**			
			Wavelet and artificial neural network			**Trial and error method [13]**
			BP	**RBF**	**PNN**	**Result**
AB	97.5	0	AB	AB	AB	AB
		10	AB	AB	AB	AB
		100	AB	AB	AB	AB
		500	AB	AB	AB	AB
ABG	97.5	0	ABG	ABG	ABG	ABG
		10	ABG	ABG	ABG	ABG
		100	ABG	ABG	ABG	ABG
		500	ABG	ABG	ABG	AB
AG	97.5	0	AG	AG	AG	AG
		10	AG	AG	AG	AG
		100	AG	AG	AG	AG
		500	AG	AG	AG	AG
ABC	97.5	0	ABC	ABC	ABC	ABC
		10	ABC	ABC	ABC	ABC
		100	ABC	AB	ABC	ABC
		500	ABC	CA	ABC	AB

4. **Conclusions.** This paper proposed a technique using discrete wavelet transform and artificial neural networks to classify fault type on single circuit transmission line. Daubechies4 (db4) is employed as mother wavelet to decompose high frequency components from fault signals. Coefficients of positive sequence current signals are calculated and employed in fault detection decision algorithm. By performing many simulations, the result is found that the fault detection decision algorithm can detect fault with the accuracy of 100% by using scale 1 only. The maximum coefficients from the first scale at 1/4 cycle of phase A, B and 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, the results issued from BP neural network, RBF neural network and PNN are compared. Various case studies have been carried out by taking into account the variation of fault inception angles and fault types. The result is shown that an average accuracy obtained from PNN is more satisfactory and has less

training time, compared with BP and RBF neural networks. The PNN is finally a better choice for high speed and accuracy in real-time application. The further work will be the investigation of the PNN for the instance loop circuits or complicated system.

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