Proceedings of the International MultiConference of Engineers and Computer Scientists 2012 Vol II,
IMECS 2012, March 14 - 16, 2012, Hong Kong

The Combination of Discrete Wavelet Transform and Self Organizing Map for Identification of Fault Location on Transmission Line

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***Abstract*— In the literature for fault location, Artificial neural networks (ANNs) have been reported. At the present time, unsupervised learning is not well understood. This paper proposes a new algorithm for identifying fault location on transmission lines, using Discrete Wavelet Transform (DWT) and Self-organizing maps (SOMs). The mother wavelet daubechies4 (db4) is employed to decompose high frequency component from these signals. The coefficients of scale1 obtained using the DWT are used for training and test processes of the SOMs. After the training process, case studies are varied. The result shows that the average accuracy obtained from combination of DWT and SOMs is satisfactory.**

***Index Terms*—Wavelet Transform, Fault Location, Transmission Line, Unsupervised network**

I. Introduction

Identifying fault location is an important problem to quickly seek out the location of fault on transmission lines to repair and maintain the power system as fast as possible in order that the transmission line can reconnect with power system. In previous papers [1-2], the travelling wave theory was applied in order to calculate the location of fault. The time that the fault signal uses to reach the ends of the transmission line is considered. Although the accuracy of fault locations from the prediction of the travelling wave theory is highly satisfactory, however, higher accuracy of fault locations is still required, thus, Artificial neural networks (ANNs) has to be investigated [3-4]. Artificial neural networks (ANNs) offer a completely different approach to problem solving, and they are sometimes called the sixth generation of computation. In the literature for fault location, ANNs have been reported. The idea of application of ANNs to fault diagnosis is not new, and there are many research papers related to this idea [2-7]. However, the most research works are interested only in back-propagation neural network (BPNN) [3] or supervised networks [4], but rarely in unsupervised networks [8-9]. One of the leaders, who involve researchers into unsupervised learning is Tuevo Kohonen. He has developed a self-organizing networks (SOMs), sometimes called an auto-associator, that learns without knowing the right answer. At the present time, unsupervised learning is not well understood. Although the BPNN or the other supervised networks have not been yet fully evaluated in comparison to SOMs but in unsupervised training, the network is provided with inputs but not with desired outputs. As a result, it is useful to be able to perform fault location on the transmission line using discrete wavelet transform (DWT) and SOMs

This paper focuses on the development of a new decision algorithm based on unsupervised neural network for fault location along the transmission line. The simulations, analysis ,and diagnosis are performed using ATP/EMTP and MATLAB on a 500 MHz, 256MB, Pentium III PC. Fault signals in each case are extracted to several scales on the discrete wavelet transforms, and then are used as an input for a training process on the neural networks. A new technique to identify fault locations on the transmission system is discussed.

II. Simulation

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

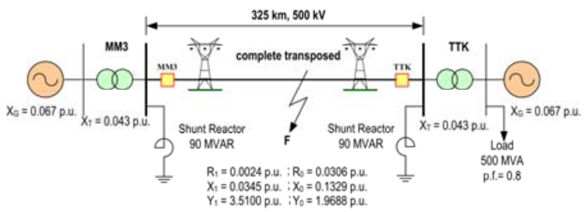

Fig. 1 The system used in simulation studies [10].

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

Manuscript received December 25, 2011.

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ISBN: 978-988-19251-9-0
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

generated using ATP/EMTP are interfaced to MATLAB for the fault detection algorithm.

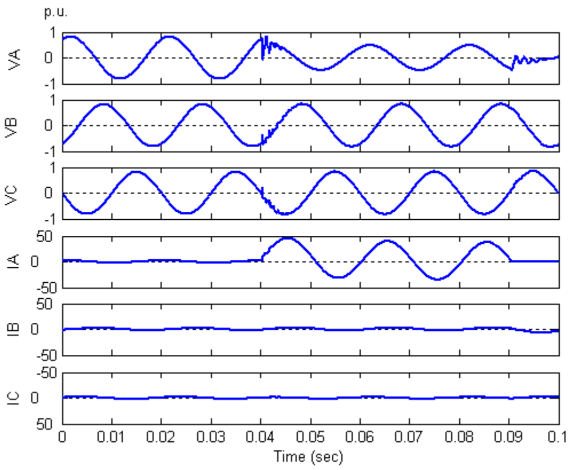

Fig. 2 Example of simulated fault signals by ATP/EMTP for AG fault at sending end.

Fault detection decision [1, 4, 11] is processed using the positive sequence current signals. The Clark's transformation matrix is employed for calculating the positive sequence and zero sequence of currents. The mother wavelet daubechies4 (db4) [1, 11-12] is employed to decompose high frequency components from the signals. Coefficients obtained using the DWT of signals are then squared to clearly identify the abrupt change in the spectra. It is evident that the coefficients of high-frequency components are abruptly changed when a fault occurs, as shown in Figure 3. The coefficients of scale 1 of DWT are used in the training processes for the neural networks in our case study.

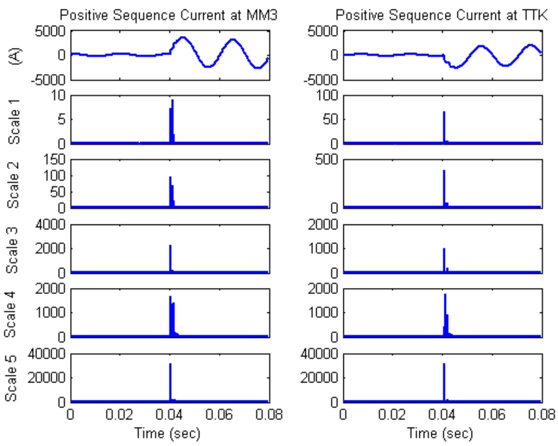

Fig. 3 Wavelet transform from scale 1 to 5 for the positive sequence of current signal shown in Fig. 2.

III. Decision Algorithm and Result

After applying the DWT, the obtained coefficients of scale 1 are used for training and test processes of the decision algorithm as shown in Figure 4. A training process is performed using neural network toolboxes in MATLAB [13]. 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 SOMs consists of 2 neurons for the inputs and 1 neuron for the output. As a mention, in previous paper, the BP was divided into two training case studies for comparing between first peak time and maximum value of DWT in order to calculate the location of fault. The results are shown that the accuracy of fault locations from the first peak time in first scale of DWT that can detect fault is highly precise so, in this paper, the first peak time in first scale of MM3 and TTK that can detect fault is considered as input patterns as shown in Figure 5.

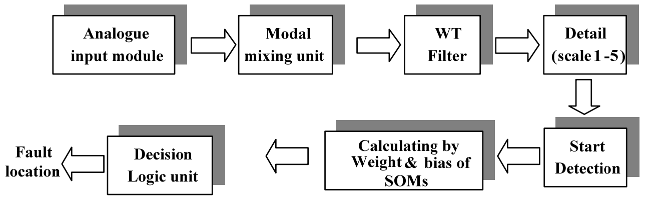

Fig. 4 The modules of identifying the fault location.

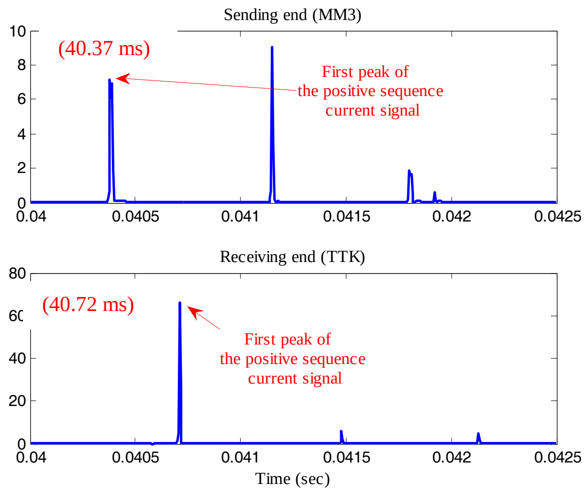

Fig. 5 First peak on the scale 1 at both ends of transmission lines for the positive sequence current

During training process, learning rate is 0.9, and number of neighborhood neurons is 1. The usual paradigm starts with a larger definition of the neighborhood, and becomes narrow when being proceeded in the training process. The distance of an input vector to each processing element is computed and the nearest element is declared as the winner, as shown in Figure 6. There is only one winner for the whole layer. Only the winner is permitted as an output, and only the winner and its neighbors are allowed to adjust their connection weights. If the winning element is in the expected class of the training vector, it is reinforced toward the training vector. If the winning element is not in the class of the training vector, the connection weights entering the processing element are moved away from the training vector.

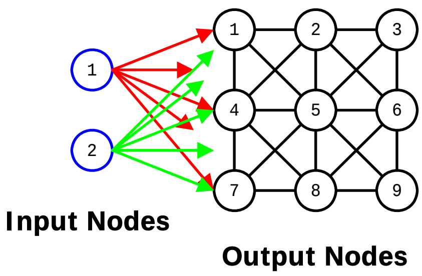

Fig. 6 SOMs with two input nodes and two-dimension (3×3 neurons)

ISBN: 978-988-19251-9-0
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

	0.5		0.4		0.3		0.2	
	0.5		0.4		0.3			0.1
	0.5				0.3		0.2	
0.8		0.8		0.6				
	0.8			0.6			0.4	
0.9			0.7		0.6			

(a) Numbers of iterations training, equivalent to10

0.1	0.1		0.3			0.5		
				0.4				0.6
0.2	0.2	0.2						0.6
			0.4			0.6	0.6	
0.3	0.3							
					0.7	0.7	0.7	
0.5				0.7		0.8		0.9
		0.5				0.8		0.9

(b) Numbers of iterations training, equivalent to 50

0.1	0.1		0.3		0.4			0.6
				0.4				0.6
0.2	0.2	0.2				0.5		0.6
			0.4		0.5		0.6	
0.3	0.3							
					0.7	0.7	0.7	
0.5				0.7		0.8		0.9
						0.8		0.9

(c) Numbers of iterations training, equivalent to 100

0.1	0.1		0.3					0.6
				0.4	0.4			0.6
0.2	0.2	0.2						0.6
			0.4		0.5		0.6	
0.3	0.3							
					0.7	0.7	0.7	
0.5				0.7		0.8		0.9
		0.5				0.8		0.9

(d) Numbers of iterations training, equivalent to 500

Fig. 7 SOMs with two input nodes and two-dimension (9×9 neurons) when varying numbers of iterations training

Table 1 summary of overall accuracy obtained from the proposed algorithms

Numbers of output nodes	Learning rate	Number of neighborhood neuron	Numbers of iterations training	SOMs	
				Training time (minute)	%Accuracy
9	0.9	1	10	0.36	77.77%
9	0.9	1	50	2.37	77.77%
9	0.9	1	100	5.12	77.77%
9	0.9	1	500	25	77.77%
36	0.9	1	10	1.1	99.44%
36	0.9	1	50	5.04	93.61%
36	**0.9**	**1**	**100**	**10.09**	**100.00%**
36	0.9	1	500	50.51	96.94%
36	**0.9**	**2**	**10**	**1.07**	**100.00%**
36	0.45	2	10	1.05	86.11%
81	0.9	1	10	2	98.88%
81	0.9	1	50	11	82.22%
81	0.9	1	100	26	82.50%
81	0.9	1	500	78	82.50%
81	0.9	2	10	2.05	99.72%
81	**0.45**	**2**	**10**	**2.08**	**100.00%**

ISBN: 978-988-19251-9-0
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

After the training process, the decision algorithm is employed in order to locate the fault in the transmission line. 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 including the variation of fault inception angles and locations in transmission line. In addition, the number of output nodes is a key factor in the SOMs training process, so the number of output nodes and learning rate are varied as shown in Figure 7. The results obtained from various numbers of output nodes are shown in Table 1 in which the results show that the new algorithm can give a better performance in predicting the fault locations.

IV. CONCLUSION

This paper proposed a new algorithm for fault location on transmission lines, using DWT and SOMs. Daubechies4 (db4) is employed as mother wavelet in order to decompose high frequency components from fault signals. The first peak times obtained from the both ends that can detect fault, are used as an input for the training process of the SOMs in a decision algorithm. Various case studies have been carried out including the variation of fault inception angles and fault types. It is shown that average accuracy obtained from combination of DWT and SOMs is satisfactory as shown in Table 1, but SOMs is complicated and the size of the neighborhood can be varied during the training period. If the size of the neighborhood is small, it is hard to classify a lot of types. 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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BIOGRAPHIES

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ISBN: 978-988-19251-9-0
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)