A Novel Wavelet-Neural Network Method for Fault Location Analysis on Transmission Lines

Reza Shariatinasab, *Member IEEE*
Electrical and Computer Eng. Dept.
University of Birjand
Birjand, Iran
shariatinasab@ieee.org

Mohsen Akbari, *Member IEEE*
Electrical and Computer Eng. Dept.
K.N. Toosi University of Technology
Tehran, Iran
mohsenakbari@ieee.org

M.R. Aghaebrahimi, *Member IEEE*
Electrical and Computer Eng. Dept.
University of Birjand
Birjand, Iran
aghaebrahimi@birjand.ac.ir

***Abstract*—This paper presents a technique, based on discrete wavelet transform (DWT) and back-propagation neural network (BPNN), to find the fault location on single circuit transmission lines. The proposed method has been applied to IEEE 9-bus test system. In order to go through this, MATLAB was used to apply DWT on the signal of fault currents of all the existed generators. The Daubechies Four (db4) mother wavelet is employed to decompose the high-frequency component of fault signals. The norm of detail coefficients of five decomposition levels for all fault current signals was selected as input pattern for the training process of a BPNN. The obtained results show that trained BPNN can be used as a proper tool to detect the location as well as the type of the occurred faults on the system, with a reasonable accuracy.**

I. Introduction

Fault location estimation is important in a power system in order to clear faults from transmission lines and to restore supply as soon as possible with minimum interruption. Distance relays respond to a ratio of voltage and current at the relay location. This ratio is in the form of impedance. Besides, the impedance of a transmission line is proportional to its length, for distance measurement. Thus, it is appropriate to use a relay that is capable of measuring the impedance of a line up to a predetermined point. In the early 1980's, the most effectiveness technique to locate fault location has been proposed based on travelling wave [1-3]. Although, travelling wave technique can give precise results in fault location, however, a high sampling rate is required, in addition to, the concern existed on distinguish between traveling waves reflected from the fault point and from the remote end of the line [4]. In order to overcome this problem, the wavelet transform (WT) of the fault transients was initially proposed in [5]. Although the WT is very effective in detecting and extracting transient events, it may not be adequate to complete the characterization.

Furthermore, during the recent years, development of fault diagnosis has been progressed with the applications of signal processing techniques and back-propagation neural networks (BPNNs) [6].

This paper aims to present a development of a new decision algorithm used in the protective relays, in order to locate fault location. The current waveforms obtained from the simulation are extracted using the WT by MATLAB. The proposed decision algorithm, presented in this paper, is constructed based on the BPNN. The BPNN inputs are selected as the norm of detail coefficients of decomposed current signals that will be discussed in the following.

II. Wavelet Analysis

WT is a well-suited tool for processing transient signals which are non-stationary and non-periodic wide-band signals. It decomposes a signal in terms of oscillations (wavelets) localized in both time and frequency. As Fourier analysis, WT consists in decomposing a given function onto a set of "building blocks". However, in contrast to Fourier transform (FT), in which the "building blocks" are the well-known complex exponentials, WT uses the dilated and translated version of a "mother wavelet" which has convenient properties according to time/frequency localization [7].

WT, also, has a special feature of variable time-frequency localization which is different from the windowed Fourier transform (WFT). Wavelet algorithms process data at different scales so that they may provide multiple resolutions in frequency and time. This ability mainly being used in this study to detect, classify and locate the faults. This property of multi-resolution is particularly useful for analyzing fault transients, which contain localized high-frequency component superposed power frequency signals. For a continuous input signal, the time scale parameters can be continuous, leading to a continuous wavelet transform (CWT). On the other hand, discrete wavelet transform (DWT) can also be defined for discrete time signals. Using the DWT, it is possible to decompose a signal into several signals in different frequency bands, which are known as wavelet coefficients. A good comparison of WFT and DWT can be found in [8].

In DWT, the mother wavelet Ψ is translated and scaled by choosing the scale and translation parameters $a=a_0^m$ and $b=nb_0a_0^m$ respectively, where a_0 (>1) and b_0 (>0) are fixed real values and m and n are positive integers. DWT of a discrete sampled signal $X(k)$ is mathematically defined as:

$$DWT_{\psi}X(m,n)=\frac{1}{\sqrt{a_0^m}}\sum_{k=-\infty}^{+\infty}X(k)\psi\left(k-\frac{nb_0a_0^m}{a_0^m}\right) \qquad (1)$$

978-1-4673-0784-0/12/$31.00 ©2012 IEEE

By (1), the main signal is separated into approximation part (a1, a2, a3, …) and detail part (d1, d2, d3, …). The approximation part is the main part of the signal and includes low-frequency components while the detail part includes high-frequency components. This trend of detail and approximation continues to each level of analysis. At each level of this successive decomposition, the parameter m in (1) is incremented to increase the frequency resolution. Good reviews of wavelets can be found in [8-10].

The frequency bands filtered out by DWT at each level are in accordance with the Mallat algorithm and Nyquist's rule. Based on the Nyquist theorem (which states that the highest frequency which can be accurately represented is less than one-half of the sampling rate), the maximum frequency of original signal $X(k)$ sampled at F Hz is $F/2$ Hz [11]. Fig. 1 shows the frequency bands at each level of DWT output.

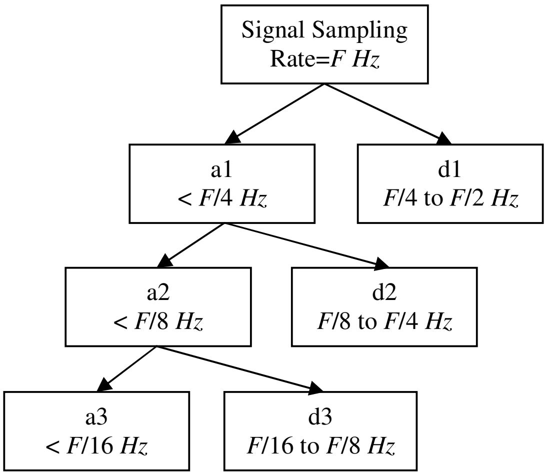

Figure 1. Frequency bands of decomposition levels in DWT

A sampling rate of F_s=10 kHz was selected for our study [12]. However, the basic concept in wavelet analysis is to select a proper wavelet, called mother wavelet (analyzing wavelet or admissible), and then perform an analysis using its translated and dilated versions. In this paper, the Daubechies four (db4) mother wavelet is selected to analyze the current signals, measured on each of the generators of test system. The approach for selecting the mother wavelet and sampling frequency was a trial-and-error procedure combined with prior experience. The successful application of 'db4' for characterizing power system transients is reported in [13].

III. Theory of Back-Propagation Neural Network (BPNN)

NNs are computational structures derived from the original biological neural structure of living beings. The basic unit of NN is a neuron, and these neurons are interconnected. Each neuron can influence other neurons through these connections. The level of influence is represented by the strength associated with the connection, technically named as the weight of the connection. Among the different connection architectures available, the most widely used for power system applications is the back-propagation type model [14-17], shown in Fig. 2. Each unit or neuron processes all the inputs and send the output to the next neuron(s) connected to it.

As shown in Fig. 2, the neurons that are directly connected to the inputs are called input layer neurons. The outputs of these neurons of the input layer are initially unknown. On the other hand, some other neurons, known as the output layer neurons are directly connected to the outputs; for these neurons the inputs are not known initially. The hidden layer neurons thus act as a bridge between the input and output layer neurons. Since the initial activation values of many of the neurons in the structure are unknown, an iterative procedure [17] is used to evaluate the best possible connection weights between neurons of the different layers. The iterations are based on a given set of input and output (target) pattern pairs, called the training sets.

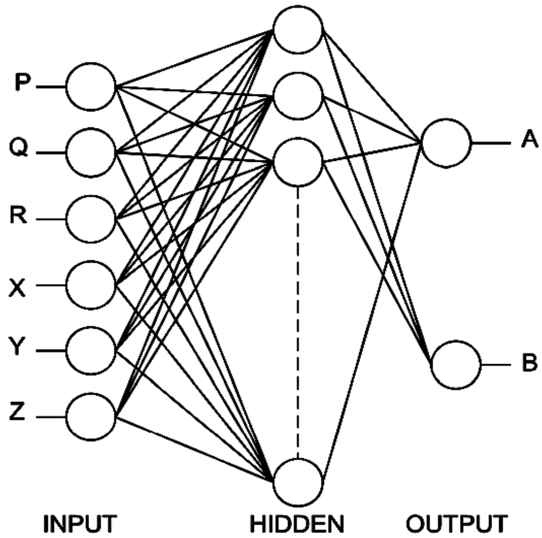

Figure 2. Back-propagation NN model

"Back-propagation" algorithm is this organized procedure based on error correction through feedback. BPNNs are highly effective for pattern recognition. It attempts to minimize error by adjusting each value of a network proportional to the derivative of error with respect to that value. This is called gradient descent. In the back-propagation learning, the actual outputs are compared with the target values to derive the error signals, which are propagated backward layer by layer for updating the synaptic weights in all the previous layers [17]. One of the most critical difficulties in constructing the NN is the choice of the number of hidden layers and the number of neurons for each layer.

Using too few neurons in the hidden layer may prevent the training process to converge, while using too many neurons would produce long training time. As well as many hidden layer neurons may result in divergence. The optimum dimension of hidden layer nodes depends on the following conditions: the numbers of input and output nodes, the number of training cases, the amount of noise in the targets, the architecture, the hidden layer node activation function and the complexity of the classification to be learned.

IV. Methodology and Study System

In this section, the proposed method for fault location analysis is applied to a system study. The IEEE 9-bus test system (Fig. 3) is selected as the study system. This system is a 400 *kV* transmission network includes three generators, and six lines, in which each line is divided to 20 points equally distanced.

A fault is applied on each of 20 points on the lines, separately. On the other hand, totally, 120 faults are applied on the network. As majority of faults occurred on transmission systems have the low fault impedance, so the fault impedance was set to zero in this study. Then, the signals of terminal currents of generators G1, G2 and G3, during the fault occurrence, were obtained by means of a 10 *kHz* sampling rate. The current signals data are obtained in a sliding-window of a quarter of cycle [18] (4.2 *ms*, 42 samples of currents). Therefore, once the fault is occurred, 42 samples of gathered data, by means of a 10 *kHz* sampling rate, are considered, i.e. equal 4.2 *ms*.

According to [19], by calculating the norm of detail coefficients of the first level (d1) for all the currents, the phase(s) on disturbance can be identified. If the calculated norm value of any phase exceeds a certain threshold, this indicates that this phase is exposed to a disturbance. The calculated norm of d1 measures the amount of energy content in d1. This norm can be calculated as [19]:

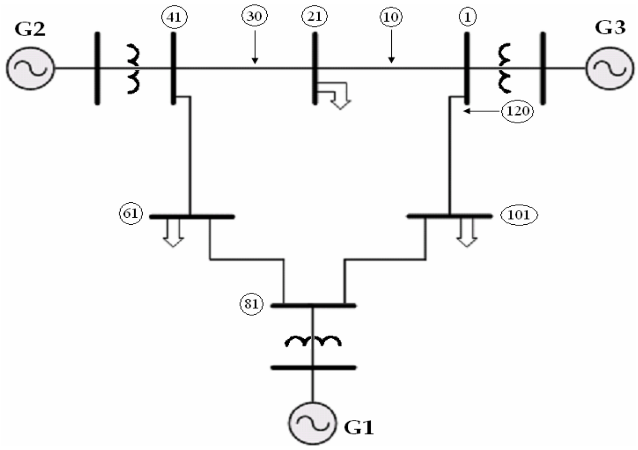

Figure 3. Schematic diagram of study system

$$\|d_1\| = \left[\sum_{k=1}^{n_d} d_1(k) \right]^{1/2} \tag{2}$$

Where n_d is the number of detail coefficients of the first level, and d1*(k)* is the *k*th coefficient of the detail coefficients of the first level.

To illustrate how a fault can be detected using WT, a single line to ground (SLG) fault (phase '*a*' to ground) on a 400 *kV* line is simulated using MATLAB/Simulink. The three phase currents are shown in Fig. 4. The calculated norm values of d1 for the current of phase '*a*', '*b*' and '*c*' are equal to 0.0106, 0.0066, 0.0042, respectively, for data window length of 210 samples. This samples number was selected to detect and classify the faults, due to give a better discrimination between faulted phases and healthy phases. It can be noticed that the norm of d1 for phase '*a*' is much higher than the values for the other two phases.

After fault detection and classification, it is necessary to extract the characteristics to provide inputs of BPNN. In order to do this, the norm of the detail coefficients of decomposed current signals was considered as BPNN inputs. To obtain the most suitable levels number of WT detail, method was implemented for 1, 2, …, 5 levels, in which the best solution was obtained with 5 levels. Therefore, the detail coefficients of 5 levels were obtained as the optimal solution to train BPNN, so that the trained BPNN can be used to locate the fault location.

To describe the method, the norm of the 5th level detail (d5) coefficients versus fault distance from a generator (G3) is illustrated in Fig. 5. As shown in Fig. 5, the far is the fault distance from G3, the lower is the norm value of coefficients. The BPNN used in this study was consisted of three hidden layers either with 20 neurons. The optimal number of neurons was determined based on the trial and error approach. The transfer functions applied in input, hidden and output layers were considered tansig, tansig and purelin, respectively, and training algorithm was also trainlm.

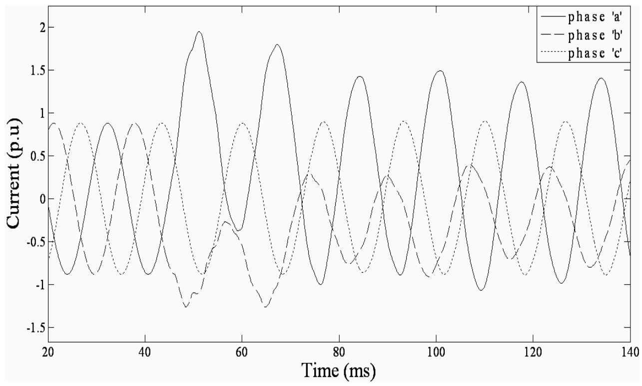

Figure 4. Three phase line currents during a SLG fault on phase '*a*'

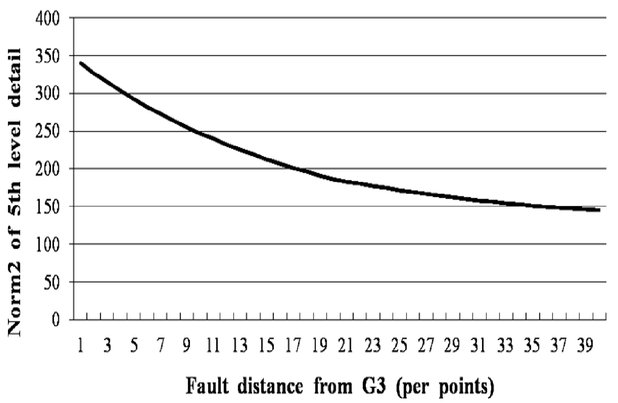

Figure 5. The norm of the 5th level detail coefficients (d5) for G3

V. Simulation Results

In order to train BPNN, faults were applied on each of the 120 nodes of system study. Nodes number is shown in Fig. 3, punctuated from G3. Then, data of 85 nodes were analyzed and used as the training patterns of BPNN, while the rest nodes, i.e. 35 nodes, were used for testing the BPNN.

According to IEEE Std. PC37.114 [20], error percentage of fault location estimation is determined as follows:

$$error\ \% = \frac{error\ \ value}{line\ \ length} \tag{3}$$

Some results obtained from the proposed DWT-BPNN technique under 3-phase faults are shown in Table I. According to the results, the resultant error is reasonable and satisfactory. Note the point of fault location is measured from G3.

As mentioned before, the time needed to find the fault location of occurrence is about 4.2 *ms*, i.e. 42 samples per 10 *kHz* sampling rate. Therefore, the method presented in this paper will be a proper technique to estimate the fault location on transmission systems.

TABLE I.
The Results of Fault Location

Point of fault location	Location estimated by BPNN	Error Value	Error %
24	23.8086	-0.1914	-0.96
34	34.0467	0.0467	0.23
49	49.0903	0.0903	0.45
57	57.1833	0.1833	0.92
11	11.1034	0.1034	0.52
66	65.7872	-0.2128	-1.06
74	74.0679	0.0679	0.34
86	86.1994	0.1994	1.00
95	94.8874	-0.1126	-0.56
103	103.2897	0.2897	1.45
112	111.7134	-0.2866	-1.43

VI. Conclusion

WT based multi-resolution analysis approach can be successfully applied for effective detection, classification and location of faults in transmission lines. Fault detection and classification can be accomplished using detail coefficients of first decomposition level of the current signal of each generator. Fault location can be estimated within 4.2 *ms* from the detail coefficients of five decomposition levels of current signals using BPNNs. Due to the obtained results, the proposed technique can be used as a fast, acceptable and successful tool for detection of the various types of the faults occurred on transmission lines, at different locations.

References

[1] P. A. Crossley, and P. G. McLaren, "Distance protection based on travelling waves," IEEE Trans. Power App. Syst., vol. PAS-102, no. 9, pp. 2971-2983, Sept. 1983.

[2] P. G. McLaren, and S. Rajendra, "Travelling wave techniques applied to the protection of teed circuits: principle of travelling wave techniques," IEEE Trans. Power App. Syst., vol. PAS-104, no. 12, pp. 3544-3550, December 1985.

[3] A. O. Ibe, and B. J. Cory, "A travelling wave based fault locator for two- and three-terminal networks," IEEE Trans. Power Del., vol. 1, no. 2, pp. 283-288, April 1986.

[4] E. H. Shehab-Eldin, and P. G. McLaren, "Travelling wave distance protection-problem areas and solutions," IEEE Trans. Power Del., vol. 3, no. 3, pp. 894-902, July 1988.

[5] F. H. Magnago, and A. Abur, "Fault location using wavelets," IEEE Trans. Power Del., vol. 13, no. 4, pp. 1475-1480, October 1998.

[6] A. Ngaopitakkul, and C. Pothisarn, "Discrete wavelet transform and back-propagation neural networks algorithm for fault location on single-circuit transmission line," Proc. the 2008 IEEE Int. Conf. Robotics and Biomimetics, pp. 1613-1618, Bangkok, Thailand, 2009.

[7] R. Shariatinasab, and M. Akbari, "New islanding detection technique for DG using discrete wavelet transform" IEEE Int. Conf. Power Energy (PECon), pp. 294-299, Kuala Lumpur, Malaysia, 2010.

[8] A. Graps, "An introduction to wavelets," IEEE Comput. Sci. Eng., vol. 2, no. 2, pp. 50–61, June 1995.

[9] I. Daubechies: Ten Lectures on Wavelets. Philadelphia, PA: SIAM, 1992.

[10] C. H. Kim and R. Agganrval, "Wavelet transforms in power systems-Part I: General introduction to the wavelet transforms," IEEE Power Eng. J., vol. 14, no. 2, pp. 81–87, Apr. 2000.

[11] T. M. Lai, L. A. Snider, E. Lo, and D. Sutanto, "High-impedance fault detection using discrete wavelet transform and frequency range and RMS conversion" IEEE Trans. Power Del., vol. 20, no. 1, pp. 397-407, January 2005.

[12] M. Michalik, M. Lukowicz, W. Rebizant, S.-J. Lee, and S.-H. Kang, "Verification of the wavelet-based HIF detecting algorithm performance in solidly grounded MV networks" IEEE Trans. Power Del., vol. 22, no. 4, Oct. 2007.

[13] R. Shariatinasab, and M. Akbari, Application of wavelet analysis in power systems, in Wavelet Transform/Book 2, edited by D. Baleanu, InTech Open Access, Rijeka, Croatia, in press.

[14] R. Shariatinasab, B. Vahidi, S. H. Hosseinian, and A. Ametani, "Probabilistic evaluation of optimal location of surge arresters on EHV and UHV networks due to switching and lightning surges," IEEE Trans. Power Del., vol. 24, no. 4, pp. 1903-1911, October 2009.

[15] R. Shariatinasab, B. Vahidi, S. H. Hosseinian, and A. Ametani, "Optimization of surge arrester's location on EHV and UHV power networks using simulation optimization method," IEEJ Trans. Power Energy, vol. 128, no.12, pp. 1465-1472, December 2008.

[16] P. S. Bhowmik, P. Purkait, and K. Bhattacharya, "A novel wavelet assisted neural network for transmission line fault analysis," Annu. IEEE India Conf. (INDICON), vol. 1, pp. 223-228, 2008.

[17] P. D. Wasserman, Neural Computing: Theory and Practice, Van Nostrand Reinhold Press: New York, 1989.

[18] F. Martín, and J. A. Aguado, "Wavelet based ANN approach for transmission line protection" IEEE Trans. Power Del., vol. 18, no. 4, pp. 1572- ,1574, October 2003.

[19] A. H. Osman, and O. P. Malik, "Transmission line distance protection based on wavelet transform" IEEE Trans. Power Del., vol. 19, no. 2, pp. 515-523, April 2004.

[20] IEEE Std. PC37.114. (2004). IEEE Guide for Determining Fault Location on AC Transmission and Distribution Lines, (2005), pp. 1-36.