ISSN 2250-3153

Estimation of an L-G Fault Distance of an Underground Cable Using WNN

Biswapriya Chatterjee

Department of Electrical Engineering, Future Institute of Engineering & Management, West Bengal, India

Abstract- In this paper we have developed a three layer Wavelet Neural Network (WNN) for L-G fault location of an underground cable. Back Propagation (BP) algorithm is used for training of the network. Simulation result and graphs shows the effectiveness of WNN as a fault locator network.

***Index Terms*-** Wavelet neural network, back propagation algorithm, underground cable system, L-G fault location

I. Introduction

Electrical energy transmission system is demanding safer and more reliable energy services. Underground cable is one of the best choices for safer and reliable power transmission. Although underground cables provide higher reliability than overhead system, in case of insulation failure it is very difficult to locate faults. To minimize such difficulties in underground system, different fault identification schemes are being evolved to locate the fault for proper remedial measures [1].

Wavelet Neural Network (WNN) is an alternative to feed forward neural network for approximating arbitrary non-linear functions. The WNN makes the best use of the good localization properties of wavelet transformation [2] and combine with the self-learning ability of neural networks [3]-[4]. Therefore WNN has better approximation and error correction abilities.

In this present work, a three layer WNN has been developed to estimate the cable fault (L-G) distance. A case study of fault currents was carried out for an underground cable for various fault location. The fault current and fault distance was chosen as input and output parameter respectively. The network was trained using back-propagation algorithm [5]. After the training has been done, the network has been tested with the tested data. Experimental graphs show that WNN can predict the fault location accurately.

II. Wavelet Neural Network

The structure of a three-layer Wavelet neural network [2], [6]-[7] with multiple inputs and multiple outputs is shown in Fig 1

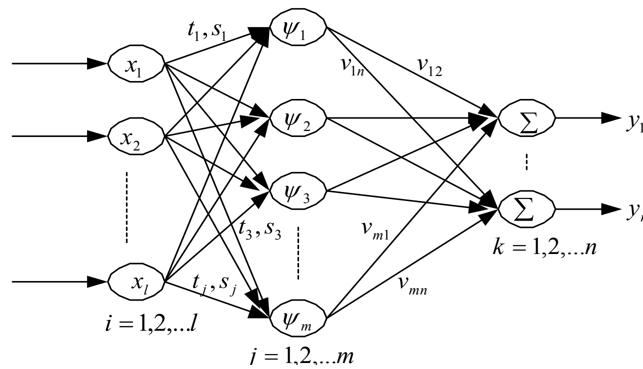

Figure 1: Wavelet Neural network

As illustrated in Fig 1 the entire network consists of three layers. First layer is called input layer which accepts the input data. The number of input nodes depends on the number of input parameters. The second layer is called hidden layer where a mother wavelet function is selected as an activation function which is Morlet wavelet for this work. Morlet wavelet function is expressed as follows [7]:

$$\psi(x) = \cos(1.75x)e^{-(1/\ 2)x^2} \tag{1}$$

Output of the WNN is calculated from the equation (2)

$$y_k(x) = [\sum_{j=1}^{m} v_{jk} * (\sum_{i=1}^{l} \psi(\frac{x_i - t_j}{s_j}))] \tag{2}$$

Where t_j, s_j denotes translation and dilation parameter respectively. v_{jk} is the weight parameters between hidden and output neurons. The weight parameters between input and hidden nodes are assumed to be unity. y_k, x_i represent k^{th} and i^{th} output and input vector respectively.

During the training session of the network, the input pattern causes output responses in each layer and hence y_k at the output layer is obtained. The difference between estimated and desired output yields an error. This error is to be minimized by feeding information forward and feeding error backward. The error function is called sum square error [7] which is described in the equation (3).

$$E = \frac{1}{2}\sum_{p=1}^{ts}\sum_{k=1}^{n}[d_k{}^p(x) - y_k{}^p(x)]^2 \tag{3}$$

where, $d_k{}^p(x), y_k{}^p(x)$ are the desired and real output of the k^{th} output node for the p^{th} training data respectively and $ts\,(p = 1,2,...,ts)$ is the total number of training sets. The equation (3) is the objective function which is minimized using back propagation algorithm. On doing so a learning technique is adopted to reduce the learning time. According to this technique modification of different network parameters viz. v_{jk}, t_j, s_j are done using the following equations (4), (5), (6) respectively.

$$v_{jk}(c+1) = v_{jk}(c) + [-\eta.\frac{\partial E_k}{\partial v_{jk}} + \mu.\Delta v_{jk}(c)] \tag{4}$$

$$t_j(c+1) = t_j(c) + [-\eta.\frac{\partial E_k}{\partial t_j} + \mu.\Delta t_j(c)] \tag{5}$$

$$s_j(c+1) = s_j(c) + [-\eta.\frac{\partial E_k}{\partial s_j} + \mu.\Delta s_j(c)] \tag{6}$$

where, η, μ are the learning rate and momentum factor respectively.

III. Underground Cable Model

The schematic diagram of an L-G fault of an underground cable in the distribution substation using a 1 km long underground HT buried cable to distribute power through an 11 kV / 415 V distribution transformers is shown in Fig 2 [8].

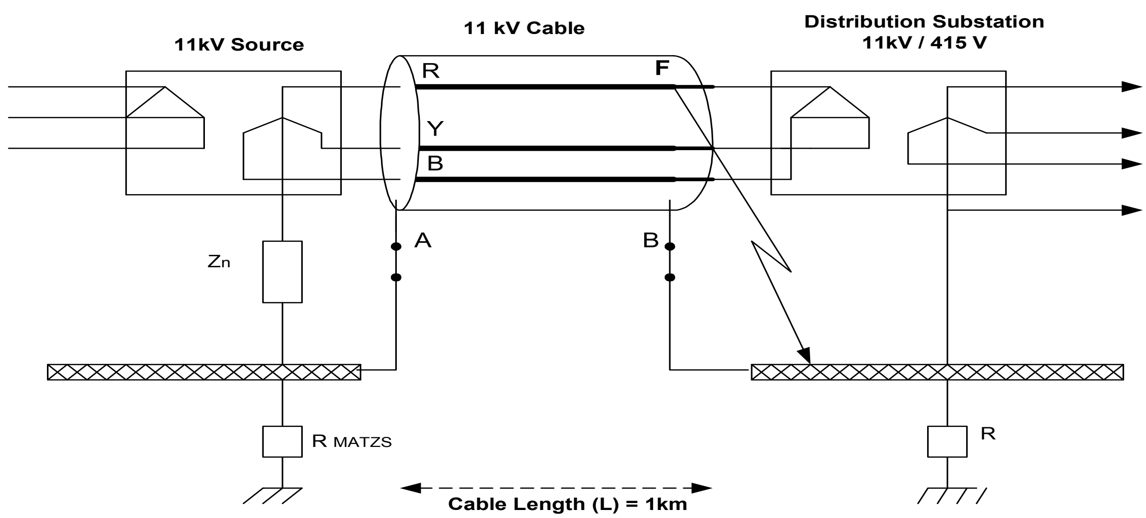

Figure 2: Schematic diagram of LG fault of an underground cable

Fault current in R-phase [9] can be found out by equation (7)

$$\therefore\ I_R = 3I_{R1} = \frac{3E_R}{Z_1 + Z_2 + Z_0} \tag{7}$$

where, E_R, I_{R1} is the pre-fault voltage and positive sequence component of fault current respectively and Z_1, Z_2, Z_0 is the positive, negative and zero sequence impedance respectively.

IV. 11 kV System Data

The 11kV system as shown in Fig 2 has three units, viz. source, 11 kV distribution cable and neutral and earthing system. The corresponding data [8] of each unit are given in Table I, II, and III respectively.

ISSN 2250-3153

Table I: Source voltage (Volts) & impedance (Ω)

Serial Number	**Parameters**	**Value**
1	Line voltage V	11 kV
2	Single phase source voltage V_{ph-n}	6350 V
3	Single phase fault level S	200 MVA
4	Positive sequence source impedance (Ω)	$Z_{s1} = j.\frac{V^2}{S} = j.\frac{11^2}{200} = j0.605$
5	Negative sequence source impedance (Ω)	$Z_{s1} = Z_{s2} = j0.605$
6	Zero sequence source impedance (Ω)	$Z_{s1} = Z_{s0} = j0.605$

Table II: 11 kV distribution cable impedance (Ω / km)

Serial Number	**Parameters**	**Value**
1	Cable size & type	150 sqmm Aluminium belted PILCPS [8]
2	Length L	1 km
3	Positive sequence cable impedance (Ω / km)	$Z_{c1} = 0.2078 + j0.0773$
4	Negative sequence cable impedance (Ω / km)	$Z_{c2} = 0.2078 + j0.0773$
5	Zero sequence cable impedance (Ω / km)	$Z_{cond\ 0} = 0.2062 + j0.1142$
6	Zero sequence sheath resistance (Ω / km)	$R_{sh0} = 2.6612$
7	Effective zero sequence impedance of the general mass of the earth (Ω / km)	$Z_{g0} = 0.148 + j2.08$
8	Fault impedance (Ω)	$Z_f = 0.0$

Table III: 11 kV neutral & earthing impedance (Ω)

Serial number	**Parameters**	**Value**
1	Neutral impedance (Ω)	$Z_n = 0.0$
2	Zone substation earthing system resistance (Ω) [8]	$R_{MATZS} = 0.01$
3	MEN impedance of typical urban extensive MEN system (Ω) [8] (MEN is equivalent to men)	$Z_{MEN} = 0.103 + j0.076$
4	Surface soil resistivity (Ω -m)	$\rho = 10$
5	Transformer earthing system resistance (Ω)	$R_e = 0.1346 \times \rho = 1.346$
6	Equivalent MEN plus R_e impedance (Ω)	$Z_{eq} = (\frac{1}{Z_{MEN}} + \frac{1}{R_e})^{-1}$ $\Rightarrow Z_{eq} = 0.1 + j0.07$

Three sequence impedances can be found out by the following equations [8]:

$$Z_1 = Z_{s1} + (Z_{cond\ 1} \times L) \quad (8)$$

$$Z_2 = Z_{s2} + (Z_{cond\ 2} \times L) \quad (9)$$

$$Z_0 = Z_{s0} + (Z_{cond\ 0} \times L) + \left(\frac{1}{R_{sh\ 0} \times L} + \frac{1}{(Z_{g0} \times L) + 3.(Z_{eq} + R_{MATZS})}\right)^{-1} \quad (10)$$

V. Result

The fault current (Phase R) is taken as input vector to the wavelet neural network. The fault distance is taken as the output vector of the network. Hence the WNN has one input and one output dimension. The network has been trained with different values of learning rate (η) momentum factor (μ), number of hidden nodes and total number of iterations. An Error versus Iteration curve is shown in Fig 3 which clearly shows that error decreases with the iteration. This proves the good converging property of wavelet neural network.

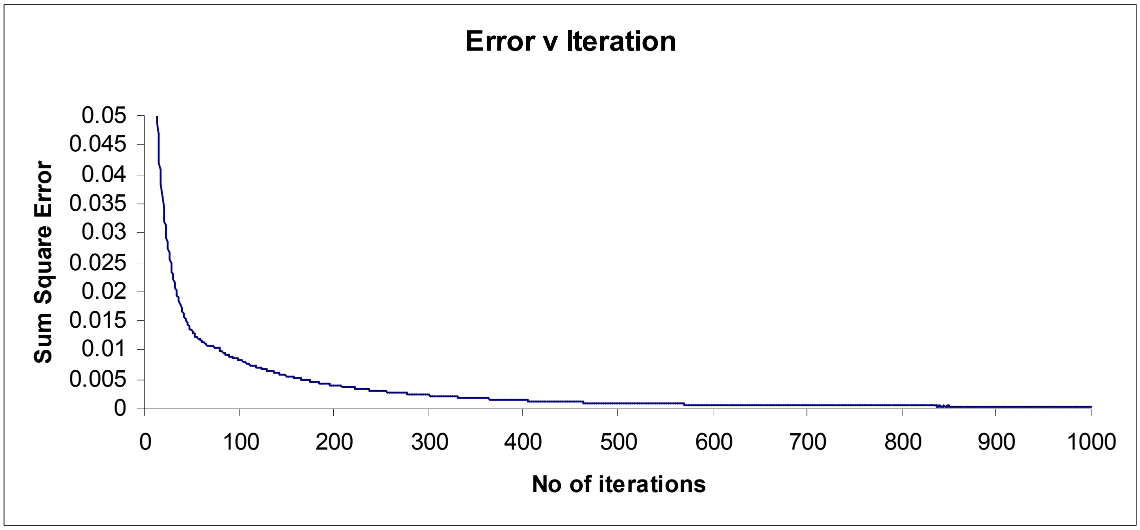

Figure 3: Sum Square Error value for different numbers of iteration

The best values of above four parameters are obtained during training process is shown in Table IV.

Table IV: Best Obtained Parameters

Learning rate	Momentum factor	No of Hidden Nodes	No of Iteration
0.09	0.09	31	3000

Using these best values of different parameters, an attempt has been made to show the accuracy of prediction between analytical and estimated output. Seventy six testing data were used for this purpose. The fault currents for different cable location are calculated for test cases. Fig 4 shows the graphical representation of analytically calculated and estimated values. This shows that analytical and estimated values represented in solid and dotted lines respectively. As both are close enough, which intern shows the capability of the wavelet neural network for fault location.

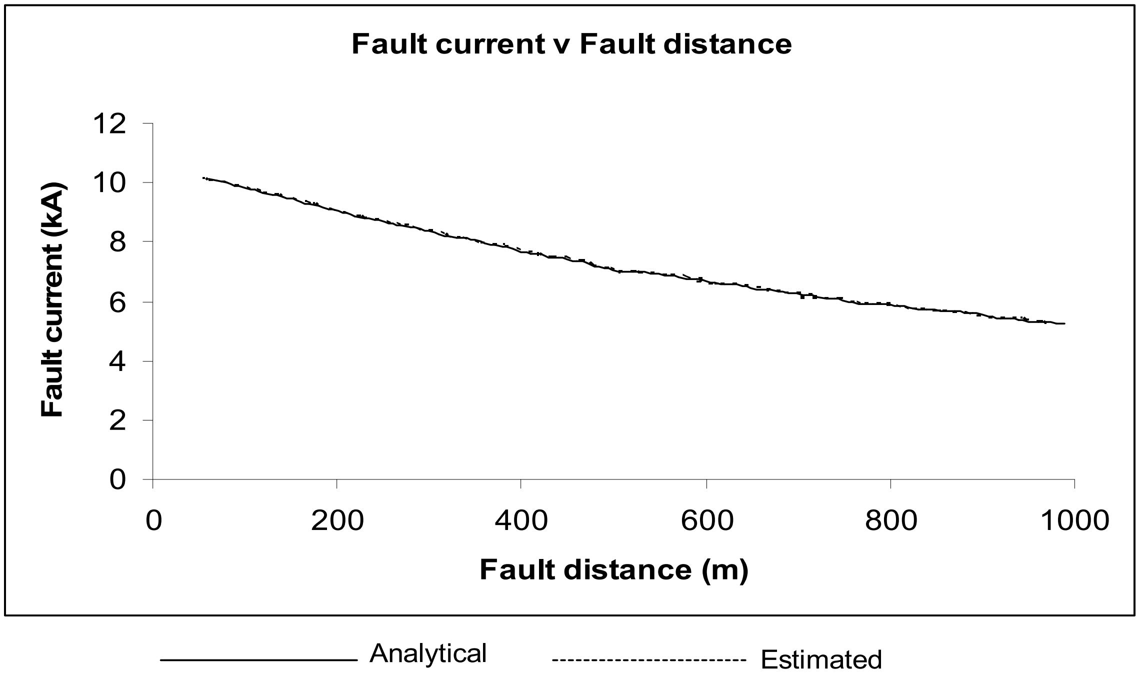

Fig 4 Analytical and estimated values of fault distance

VI. CONCLUSION

In this paper we designed back propagation algorithm based wavelet neural network to estimate cable fault (L-G) distance. Detailed studies have been made to determine the effects of various network parameters, viz. learning rate (η), momentum factor (μ), number of wavelons, and number of iterations on convergence of the training process which was implemented by BP algorithm. It has been observed that the WNN has given an accurate prediction of fault distance by using these optimum values of network parameters.

REFERENCES

[1] H.K. Zadeh, "An Accurate Fault Locator for Cable Transmission Using ANN", Electrotechnical Conference of 12th IEEE Mediterranean, Melecon, Vol. 3, pp. 901-904, 2004.

[2] Z. Kun, and C. W. Kai, "On-Line Fuzzy Adaptive Controller with Wavelet Neural Network", IEEE Proceedings, ICII 2001- Beijing , China, Vol. 4, pp. 394-399, 2001.

[3] A. K. Pradhan, A. Routray, and A. Behera, "Power Quality Disturbance Employing Modular Wavlet Network", IEEE Conference on Power Engineering Society, Malaysia, 2006.

[4] K. Karthikeyan, "A Comparative Study on the Performance of ANN, WNN, and PSO Aided WNN for Estimation of Complex Functions in High Voltage System", MEE Thesis, Jadavpur University, India, June 2007.

[5] Charu Gupta, "Implementation of Back Propagation Algorithm (of neural networks) in VHDL", Master of Engineering Thesis, Thapar Institute of Engineering & Technology (Deemed University) ,Patiala, India, June 2006.

[6] B.B. Mishra, P.K. Das, and G. Panda, "Pattern Classification Using Local Linear Wavelet Neural Network", IEEE Proceedings of International Conference on Information and Communication Technology, Dhaka, Bangladesh, pp. 92-95, 2007.

[7] Z.Y. Luo, and Z.K. Shi, "Wavelet Neural Network for Fault Diagnosis of Push-Pull Circuits", IEEE Proceedings of International Conference on Machine Learning and Cybernetics, Guangzhou, China, Vol. 6, pp. 3327-3332, August 2005.

[8] "Extensive Urban MEN System Supplied by a HV Buried Cable" by http://www.nzccpts.co.nz/.../Mathead%20%20HB%20219%20Worked%20 Example%203.7.1.%20(NZ).pdf.

[9] J.B. Gupta, "A Course in Power Systems", by S.K. Kataria & Sons.

AUTHORS

First Author – Biswapriya Chatterjee, M.Tech. Assistant professor of Department of Electrical Engineering, Future Institute of Engineering & Management, West Bengal, India

Correspondence Author – Biswapriya Chatterjee, M.Tech. Assistant professor of Department of Electrical Engineering, Future Institute of Engineering & Management, West Bengal, India

Phone No : 2483-8236
Email address : biswaee@gmail.com