Accurate Fault Location of EHV Teed Feeder using RBFNN

Eyada A. J. Alanzi , Prof. Mohd Zaid Abdullah , Dr. Nor Ashidi Mat Isa

SCHOOL OF ELECTRICAL & ELECTRONICS ENGINEERING
UNIVERSITY SAINS MALAYSIA
14300 NIBONG TEBAL, PULAU PINANG, MALAYSIA

Summary
This paper presents a new technique of accurate fault location system using artificial neural networks (ANN) for EHV teed feeder transmission lines. This technique utilizes voltage and current waveforms from one side of the three branches of the network to determine the accurate fault location. Variety of fault conditions are analyzed, trained and tested by the radial basis function neural network (RBFNN) using MATLAB. Fault detection, branch determination, fault classification and fault location are practiced. Results are obtained from training and testing of RBFNN and using ATP-EMTP for simulation of faulted data from a 500KV teed feeder transmission system.

Key words:
Fault locator, Teed feeders, RBFNN.

1. Introduction

Fault location technique in transmission lines has a great advantage to clear the fault quickly and restore the power in a timely manner. Conventional techniques of fault location in power transmission systems suffer a number of problems, due to infeed from remote end and fault resistance. Similarly, teed feeders have more problems which are mainly related to the intermediate infeed from the third terminal, outfeeds, difference in line length to tee point and different source impedances [1]. Most of the work reported so far has been concerned with two terminal lines with less attention to teed feeders transmission lines configurations. These earlier studies proposed mainly two different techniques based on traveling wave theory and Wavelet analysis [2]. The main problems of the traveling wave method is that it requires high sampling rates and has a difficulty in distinguishing between traveling waves from both the fault and the remote end of the line [3]. The wavelet transform analysis is based on the high-frequency components of the faulted signals on each terminal of the system. The limitation stated is that at low signal-noise ratio (SNR), the method becomes inefficient. In all past studies voltages and currents waveforms are captured at all the three ends of the teed feeders which can affect the accuracy due to data synchronization problem [1]. This paper presents a new technique to determine the accurate fault location of EHV teed feeder using a single-ended artificial neural network (ANN) locator. Single-ended fault location method is preferred due to its simplicity, fast accomplishment and less communication requirement [4]. Also, the problem of data synchronization is eliminated.

ANN-based techniques show a great enhancement in the accuracy of fault location with comparison to the conventional techniques [5]. This is due to the new features of ANN which are not existing in the conventional methods such as the capability of non-linear mapping, parallel processing and learning.

The technique uses radial basic function (RBF) neural networks for determination of the faulted branch, classification of the fault type and locating of the fault on the teed feeder. The locator captures voltages and currents waveforms of the faulted data at one end only of the three branches. The neural network fault locator was trained and tested with a number of simulation cases by considering various fault conditions (faulted branch, fault type, fault location, fault resistance and fault inception angles).

2. Radial Basis Function Neural Network (RBFNN)

Radial basis function neural network (RBFNN) consists of three layers with entirely different roles. The input layer is made of source nodes that connect the network with its environment. The second layer, the hidden layer in the network that possesses an array of neurons called the computing units. The number of these units can be varied depending on users' requirement. In most applications the hidden layers is of high dimensionality. The third layer is the output layer. The structure of RBFNN is shown in Fig.1.

Manuscript received December 5, 2007
Manuscript revised December 20, 2007

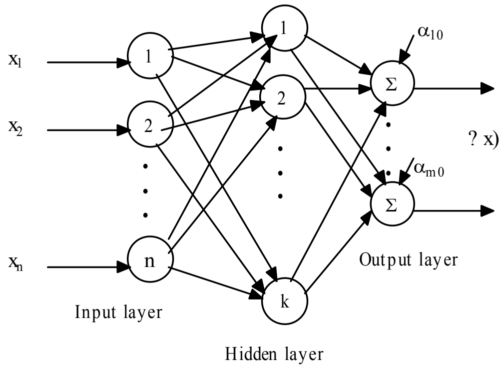

Fig.1 The structure of RBF Neural Network

Different basis functions like spline, multiquadratic, Gaussian functions have been studied, but most widely used one is the Gaussian type.
In comparison to the other types of neural network used for pattern classification like back propagation feed forward networks, the RBF network requires less computation time for learning and has a more compact topology. The Gaussian RBF is found suitable in generalizing a global mapping but also in refining local features without altering the already learned mapping. The network starts with no hidden units and adds units till a minimal radius is obtained by updating the parameters of the Gaussian function and the weights. Each hidden units in the network has two parameters called a center (μ) and a width (σ) associated with it. The response of one such hidden unit to the network input x_n is expressed as

$$\phi_\kappa (x_n) = \exp\left(\frac{-1}{\sigma^2_\kappa} \| x_n - \mu_\kappa \|^2 \right) \qquad (1)$$

Where $\mu_\kappa$is the center vector for κth hidden unit and σ_κ is the width of the Gaussian function, $\|\ \|$ denotes the Euclidean norm. The output layer comprises a number of nodes depending on the number of fault types to be classified which perform simple summation. The response of each hidden unit (1) is scaled by its connecting weights (α's) to the output nodes and then summed to produce the overall network output. The overall network output is expressed as

$$f_m(x_n) = \alpha_{m0} + \sum_{\kappa=1}^{K} \alpha_{m\kappa}\, \phi_\kappa (x_n) \qquad (2)$$

Where K indicates the total number of hidden neurons in the network, α_{mk} is the connecting weight of the κth hidden unit to mth output node and α_{m0} is the bias term for the corresponding mth output neuron.

The learning process of the RBFNN involves with the allocation of new hidden units and tuning of network parameters. The learning process is terminated when the output error goes under the defined threshold [6].

3. Power System Under Consideration

The system under study is a 500 KV teed feeder overhead transmission lines and the power system frequency is 50 HZ. It consists of three branches of 500 KV with generation sources at each end and all the three lines are connected at a tee joint. Typical network parameters have been adopted. Lengths of all three branches are shown in Fig.2.

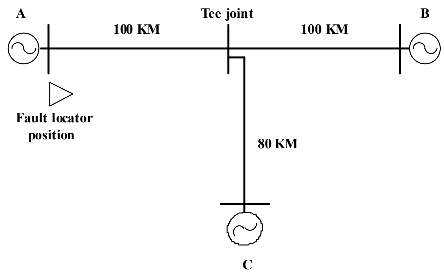

Fig.2 Teed feeder transmission system

4. Design Process of the Required Fault Locator

Fault location technique is based on utilizing voltage and current waveforms at the fault locator position in training and testing of data. The faulted waveforms will be simulated and generated by the well known and approved software (ATP-EMTP) Alternative Transient Program - ElectroMagnetic Transient Program. Pre-processing is used to extract the necessary information in a properly useful form. The waveform signals are filtered using anti-aliasing digital filter to attenuate the DC and high frequency components. Voltage and current values are normalized in the intervals [-1,+1] before being applied by the RBFNN software for training and testing.
The model of the proposed fault location technique is shown in Fig.3. It consists of three modules that lead to accurate fault location using the RBFNN approach.

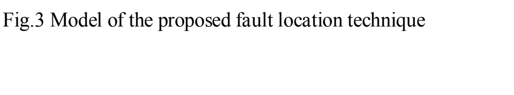

Fig.3 Model of the proposed fault location technique

This paper considered the following types of faults on each of the three branches of the teed feeder system:
1. Single line to ground fault
2. Line to line fault
3. Line to line to ground fault
4. Three phase to ground fault

For each fault type, two parameters have been considered:
1. Inception fault angle, [0°,90°], and
2. Fault resistance in ohms, [0Ω,100Ω].

Next, each module is discussed with the application of RBFNN and results are tabulated and analyzed.

5. Faulted Branch Determination

The determination of faulted branch technique is based on training of all considered types of faults (SLG, LL, LLG and 3LG) with all considered parameters (inception angles and fault resistances) for each type of fault. The results in the tables below is presented for each type of fault separately for the faulted branches determined by RBFNN approach with a high precision in each case. The effects of different inception angles and fault resistances and fault types are also shown for each case. From these results, it is clear that the accuracy of achieving faulted branch is very high in most cases. Moreover, the results demonstrate the importance of overall accuracy of the proposed technique over the previous mentioned conventional techniques. Table.1 show the results of calculated branches during SLG fault with different fault inception angles and fault resistances.

Table.1. Faulted branch determination during SLG fault

Inception angle (◦)	Fault resistance (Ω)	Actual branches			Estimated branches		
		1	2	3	1	2	3
0	0	1	0	0	1.04	0.03	0.01
0	0	0	1	0	0.008	0.99	0.01
0	0	0	0	1	0.27	0.48	1.21
0	100	1	0	0	1.001	0.005	0.001
0	100	0	1	0	0.028	1.038	0.01
0	100	0	0	1	0.048	0.047	1.001
90	0	1	0	0	0.999	0.001	0
90	0	0	1	0	0	1	0
90	0	0	0	1	0	0	1
90	100	1	0	0	0.999	0	0
90	100	0	1	0	0	0.999	0
90	100	0	0	1	0	0	0.999

Table.2, Table.3 and Table.4 illustrate the results of estimated branches of the teed feeder system during LL, LLG and 3LG faults with consideration of different fault inception angles and fault resistances. It is clear from the results that the fault locator provide an inherently accurate determination of faulted branches of the teed feeder system independent of fault inception angles and fault resistances variations.

Table.2. Faulted branch determination during LL fault

Inception angle (◦)	Fault resistance (Ω)	Actual branches			Estimated branches		
		1	2	3	1	2	3
0	0	1	0	0	1.0007	0.001	0.002
0	0	0	1	0	0.002	1.038	0.036
0	0	0	0	1	0.0145	0.048	0.966
0	100	1	0	0	0.990	0.030	0.020
0	100	0	1	0	0.0016	0.980	0.021
0	100	0	0	1	0.0014	0.005	0.995
90	0	1	0	0	1.001	0.000	0.000
90	0	0	1	0	0.013	0.962	0.050
90	0	0	0	1	0.2139	0.155	1.058
90	100	1	0	0	1.001	0.000	0.000
90	100	0	1	0	0.013	0.962	0.050
90	100	0	0	1	0.2186	0.161	1.057

Table.3. Faulted branch determination during LLG fault

Inception angle (◦)	Fault resistance (Ω)	Actual branches			Estimated branches		
		1	2	3	1	2	3
0	0	1	0	0	1.0233	0.0103	0.013
0	0	0	1	0	0.6301	1.1817	0.448
0	0	0	0	1	1.1819	0.927	1.254
0	100	1	0	0	1.0033	0.0176	0.014
0	100	0	1	0	0.0011	1.0034	0.004
0	100	0	0	1	0.0041	0.0189	0.977
90	0	1	0	0	1.0028	0.003	0
90	0	0	1	0	0.0255	1.0149	0.010
90	0	0	0	1	0.0412	0.0094	1.031
90	100	1	0	0	1.0071	0.0053	0.001
90	100	0	1	0	0.0022	1.0032	0.001
90	100	0	0	1	0.0011	0.0007	1

Table.4. Faulted branch determination during 3LG fault

Inception angle (◦)	Fault resistance (Ω)	Actual branches			Estimated branches		
		1	2	3	1	2	3
0	0	1	0	0	1.0025	0.019	0.0215
0	0	0	1	0	0.789	1.437	0.3528
0	0	0	0	1	0.538	0.697	1.5682
0	100	1	0	0	1.0098	0.036	0.0261
0	100	0	1	0	0.0517	1.0294	0.0223

0	100	0	0	1	0.0103	0.0012	1.0092
90	0	1	0	0	1.0001	0	0.0001
90	0	0	1	0	0.0396	0.9966	0.0431
90	0	0	0	1	0.1543	0.0832	1.0711
90	100	1	0	0	1.0008	0.0011	0.0003
90	100	0	1	0	0.0008	0.9995	0.0003
90	100	0	0	1	0	0.0001	1.0001

6. Fault Type (FT) and Fault Location (FL) Determination

The two modules of the fault type (FT) detection and the fault location (FL) are taken into one step by the RBFNN technique and showed accurate results. Fault types are represented by numbers as shown in Table.5 for easy illustration of the results in Table.6 and Table.7.

Table.5. Fault types (FT) presentation by numbers

SLG fault	LL fault	LLG fault	3LG fault
1	2	3	4

6.1 Effect of Fault Resistance

Table.6 illustrate the results of neural network for the fault type and the fault location being extracted in one step with the % error. It is apparent from the high accuracy of the results that the variation in the fault resistance has a negligible effect on the estimated data of the proposed technique.

Table.6. Estimated fault type and fault location at different fault resistances

Fault Resistance (Ω)	Actual		Estimated		%Error
	FT	FL (km)	FT	FL (km)	
0	1	17	0.9993	16.9853	0.00735
	2	42	1.999	42.0059	0.00295
	3	63	2.999	63.1036	0.0518
	4	76	3.999	76.0539	0.02695
100	1	17	0.9996	16.97	0.015
	2	42	2	41.9982	0.0009
	3	63	3.001	62.9073	0.04635
	4	76	4.0011	76.0687	0.03435

$$\%\mathbf{Error} = \frac{\textbf{(Estimated Location – Actual Location)}}{\textbf{Total length of the line}} \times 100$$

6.2 Effect of Fault Inception Angle

The fault locator is tested at different fault inception angles. Table.7 show the accuracy of estimated fault type and fault location with variation of fault inception angles. It is clearly evidence from the tabulated results that the accuracy achieved in fault type and fault location is very high where the %error is less than 0.05% in the majority of the cases.

Table.7. Estimated fault type and fault location at different fault inception angles

Fault inception angle (°)	Actual		Estimated		% error
	FT	FL (km)	FT	FL (km)	
0	1	17	1.0003	16.9961	0.00195
	2	42	2.0032	42.112	0.056
	3	63	3.0004	63.0226	0.0113
	4	76	3.9994	75.9745	0.01275
90	1	17	1	17.0001	0.00005
	2	42	2	41.9995	0.00025
	3	63	3.005	63.2971	0.14855
	4	76	4	76.0001	0.00005

7. Conclusion

An efficient fault location technique using RBF neural network for EHV teed feeder transmission lines has been presented. The results demonstrated the ability of RBFNN to provide a high accuracy for the majority of practically encountered teed feeder systems. It also illustrated the effectiveness and high precision of determination and detection of fault location over different branches of the teed feeder system in a variety of fault situations including fault types, fault inception angles and fault resistances. The neural network technique uses the transient faulted waveforms (voltages and currents) from one end only to detect the fault location among the three branches of the teed feeder system.

References

[1] R. K. Aggarwal, D. V. Coury, A. T. Johns, and A. Kalam, "A practical approach to accurate fault location on extra high voltage teed feeders". IEEE – Trans. Power Delivery, vol.8. pp.874-883, Jul. 1993.

[2] L. L. Lai, E. Vaseekar, H. Subasinghe, N. Rajkumar, A. Carter, and B. J. Gwyn, "Application of wavelet transform and neural networks to fault location of a teed-circuit". IEE Colloquium on Time-scale and Time-Frequency Analysis and Applications, London, Feb. 2000.

[3] M. da Silva, M. Oleskovicz, and D. V. Coury, "A Fault Locator for Three-Terminal Lines Based on Wavelet Transform Applied to Synchronized Current and Voltages Signals". IEEE PES Trans. And Distr. Conf. and Exposition Latin America, Venezuela, 2006.

[4] D. A. Tziouvaras, J. B. Robrts, and G. Benmouyal, "New Multi-ended Fault Location Design for two- or three-

terminal lines". In Proc. 2002 IEE Development in Power System Protection Conference, pp.395-398.
[5] M. Joorabian, S. M. A. Taleghani Asl, and R. K. Aggarwal, "Accurate fault locator for EHV transmission lines based on radial basis function neural networks". Elsevier, Electric Power Systems Research 71 (2004), pp.195-2002.
[6] P. K. Dash, A. K. Pradhan, and G. Panda, "Application of Minimal radial basis function neural network to distance protection". IEEE Trans. Power Deliv.,vol.16,No.1, Jan. 2001, pp.68-74.

Eyada A. J. Alanzi received the B.E. and M.E. degrees, from Kuwait Univ. in 1985 and 1996, respectively. He worked in the private sector for more than 20 years on design and construction of Electrical Projects. He is currently working on his research as PhD candidate in the School of Electrical and Electronic Engineering, Univesiti Sains Malaysia (USM). His research interest includes power systems, neural networks and their application to fault locations. He is a member of IEE - UK (Chartered Engineer) and IEEE - USA.

Prof. Mohd Zaid abdullah graduated from University Science Malaysia (USM) with a B.App. Sc. degree in Electronics in 1986 before joining Hitachi Semiconductor (Malaysia) as a Test Engineer. In 1989 he commenced an M.Sc. in Instrument Design and Application at UMIST. He remained in Manchester, carrying out research in Electrical Impedance Tomography at the same university, and received his Ph.D. degree in 1993. He returned to Malaysia in the same year to start a career as a lecturer with USM. His research interests include digital image processing, computer vision and electromagnetic sensing. He has published numerous research articles in international journals and conference proceedings. One of his papers was awarded The Senior Moulton medal for the best article published by the Institute of Chemical Engineers in 2002. Presently he is a Professor and the Dean of the USM's School of Electrical and Electronic Engineering.

Dr. Nor Ashidi Mat Isa obtained his B.Eng Hons (First Class Honors) in Electrical and Electronic Engineering from Universiti Sains Malaysia in 2000 and PhD in Image Processing and Neural Networks from the same university in 2003. He is currently a senior lecturer and lecturing at the School of Electrical and Electronics Engineering, USM Engineering Campus in Nibong Tebal, Penang, Malaysia. He specializes in the area of image processing, neurral networks, medical imaging, biomedical engineering and algorithms.