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Fault Diagnosis of Parallel Transmission Lines Using Wavelet Based ANFIS

[1]R. Rajeswari, [2]N. Kamaraj and [3]K.S. Swarup
[1]Department of Electrical Engineering, Alagappa Chettiar Engineering, College of Karaikudi, Tamilnadu, India
[2]Department of Electrical Engineering, Thiagarajar College of Engineering, Madurai-625 215, Tamilnadu, India
[3]Department of Electrical Engineering, I.I.T. Madras, Chennai 600036, Tamilnadu, India

Abstract: A new scheme to enhance the solution of the problems associated with parallel transmission line protection is presented in this study. This study demonstrates a novel application of wavelet transform to identify faults in parallel transmission line. The discrimination scheme which can automatically recognize the type of fault is proposed using ANFIS. The scheme can be separated into 2 stages, the time-frequency analysis of transients by wavelet transform and the pattern recognition to identify the type of fault. By using the actual fault data, it is shown that the proposed method provides satisfactory results for identifying the faults.

Key words: Distance protection, wavelet transform, Adaptive Neuro Fuzzy Inference System (ANFIS)

INTRODUCTION

Distance protection relaying algorithms are commonly applied for the protection of overhead transmission lines. Their operation is based on measuring the input impedances of the lines using the voltage and current signals at the relay location. The input impedance of a short-circuited line varies from zero for a fault at its input terminals to a finite value for a fault at its remote end, the value of the impedance increasing with the distance to the fault. This relaying technique can successfully be applied for single-circuit lines. However, when applied to parallel lines, the performance of the conventional distance relays is affected by the mutual coupling between the lines. The mutual inductance between pairs of conductors in the 2 lines is not the same and, therefore, emfs are produced in the conductors of the other line. As a result, the apparent input impedance of a line on which a fault is present is affected by load currents or currents being fed to the fault by a parallel healthy line and the operation of the distance relay can be affected.

A scheme based on using one relay at one end of the parallel transmission line is proposed in this study. Figure 1 shows the sample power system model. Any single phase current of one transmission line is needed for this algorithm. Using Wavelet transform, (Fernando and Ali, 1998; Heydt and Galli, 1997) features are extracted from faulty current signals. And these are used in ANFIS for detecting type of fault in the line. Simulation studies illustrate the effectiveness of this scheme.

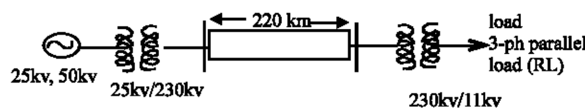

Fig. 1: Sample power system

WAVELET TRANSFORM

Wavelet transform was introduced at the beginning of the 1980s and has attracted much interest in the fields of speech and image processing since then. Its potential applications to power industry have been discussed recently (Wai and Yibin, 1998; Robertson *et al*., 1996; Hongkyum *et al*., 2004). All four studies are discussing about use of wavelet for signal processing. In this approach, any function f (t) can be expanded in terms of a class of orthogonal basis functions. In wavelet applications, different basis functions have been proposed and selected. Each basis function has its feasibility depending on the application requirements. In the proposed scheme, dmey wavelet was selected to serve as a wavelet basis function for extracting features from faulty currents.

Corresponding Author: R. Rajeswari, Department of Electrical Engineering, Alagappa Chettiar Engineering College, Karaikudi, Tamilnadu, India

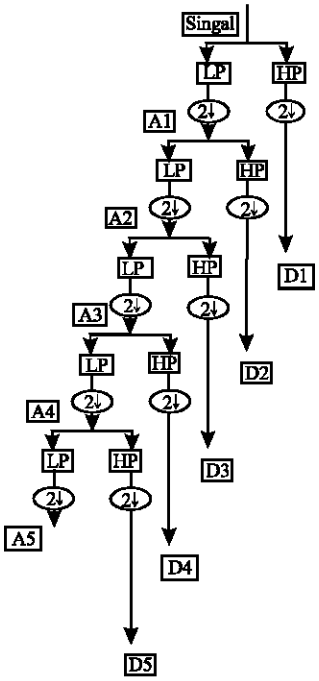

Fig. 2: WT multiresolution algorithm

Figure 2 shows the tree algorithm of a multiresolution WT for a signal (Osman and Malik, 2004) discussing about the use of WT for protection of parallel transmission lines. The outputs of the LP filters are called the Approximation (A) and the outputs of the HP filters are called the Details (D). There are 2 fundamental equations upon which wavelet calculations are based; the scaling function ΦΨ∑∫ε Φ(t) and the wavelet function Ψ(t)

$$\Psi(t) = \sqrt{2}\sum_{k} g_{k_\Phi}(2t-k)$$

$$\Phi(t) = \sqrt{2}\sum_{k} h_{k_\Phi}(2t-k)$$

These functions are two-scale difference equations based on a chosen scaling function Φ, with properties that satisfy certain admission criteria. The discrete sequences hk and gk represent discrete filters that solve each equation. The scaling and wavelet functions are the prototype of a class of orthonormal basis functions of the form

$$\Phi_j,k(t) = 2^{j/2}\,\Phi(2^j t - k) \qquad j,k\ \varepsilon\ z$$

$$\Psi(t) = 2^{j/2}\,\Psi(2^j t - k) \qquad j,k\ \varepsilon\ z$$

Where the parameter j controls the dilation or compression of the function in time scale and amplitude, the parameter k controls the translation of the function in time, and z is a set of integers.

Once a wavelet system is created, it can be used to expand a function f (t) in terms of the basis functions

$$f(t) = \sum_{l\varepsilon z} c(l)\,\Phi_l(t) + \sum_{j=0}^{J-1}\sum_{\varepsilon z}^{\infty} d(j,k)\,\Psi_{j,k}(t)$$

Where the coefficients c (l) and d (j,k) are calculated by inner product as

$$c(l) = \langle \Phi_l \mid f \rangle = \int f(t)\,\Phi_l(t)\,dt$$
$$d(j,k) = \langle \Psi_{j,k} \mid f \rangle = \int f(t)\,\Psi_{j,k}\,dt$$

The expansion coefficients c(l) represent the approximation of the original signal f(t) with a resolution of one point per every 2^J points of the original signal. The expansion coefficients d(j,k) represent details of the original signal at different levels of resolution. c(l) and d(j,k) terms can be calculated by direct convolution of f(t) samples with the coefficients h_k and g_k.

BASIC THEORY OF ANFIS

Adaptive Neural Fuzzy Inference System (ANF1S) is a product by combining the fuzzy inference system with neural network. Use of ANFIS for identifying nonlinear system is discussed by ZhixiangHai *et al*. (2003). The fuzzy inference system is used widely in fuzzy control, it can number rules by leading into a new ideal of membership function to deal with structural knowledge. Neural network usually don't deal with structure knowledge, but it has the function of self-adapting and self-learning, by learning a lot of data, it can estimate the relations between the data of input and output and has strong inundate function. ANFIS fully makes use of the excellent characteristics of neural network and fuzzy inference system and is widely applied in fuzzy control and model discerning fields. As a special neural network**,** ANFIS can approach all nonlinear-system with less training data and quicker weakening speed and higher precision. ANFIS is a neural network in fact, which realize sugeno system using network. Thinking of a system with *N* input and 1 output, each input is divided into M fuzzy sets, M^N fuzzy rule of sugeno model as following:

If x_1 is A_{1i1} and x_2 is A_{2i2}…. and x_N is $A_{N\times N}$
Then $y_{i1i2\ldots,iN} = {}_k{}^N{=}1\, p_{i1i2\ldots iN}{}^{(k)} x_k + q_{i1i2\ldots iN'}$
i1, i2, i3..., iN ∈ {1, 2….M}

The structure of ANFIS (N = 2, M = 3) is shown in Fig. 3 and the junction spot of same layer have same kind output function, the detail of whole network as following:

The 1st layer: The output function of each junction spot as following:

$$O^{(1)}_{kik} = \mu_{kik}(x_k)$$
$$k = 1, 2... N \; i_k = 1, 2 ...M$$

Where x_k is the input of the k,i_k junction spot and A_{kik} is language fuzzy sets and $O^{(1)}_{kik}$ is membership function of xk, where membership function includes some parameter, taking a example, bell form function as following

$$\mu_{A\,N}(x) = (1+|(x- c_{ik})/a_{kik}|^{2bkk})^{-1}$$

its form depends on three parameter $\{a_{kik}, b_{kik,} c_{kik}\}$

The 2nd layer: The layer has M^N junction spot and the output of each junction spot is the product of all input multiplied, but the multiplication may be instead of all kinds of T-model plan egg. The output of this layer as following:

$$O^{(2)}_{i1i2...iN} = {}^{N}{}_{k=1} O^{(1)}_{kik} = {}^{N}{}_{k=1} \mu_{kik}(x_k)$$

$$i_1, i_2, .. \; i_N = 1,2,..M$$

The 3rd layer: This layer has the same junction spots as the second layer, the output of this layer as following:

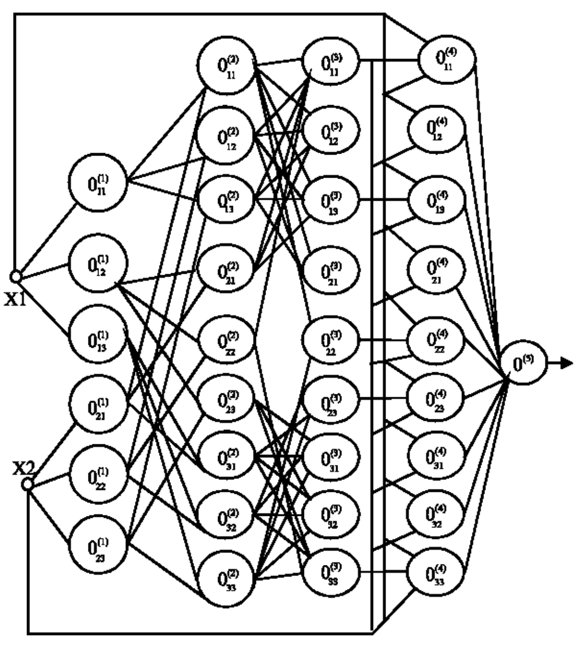

Fig. 3: Structure of ANFIS (N = 2, M = 3)

$$O^{(3)}_{i1i2...iN} = O^{(2)}_{i1i2...iN} / {}^{M}{}_{i1i2...iN=1} O^{(2)}_{i1i2...iN}$$
$$= ({}^{N}{}_{k=1} \mu_{Akik}(x_k)) / {}_{i1i2...iN} {}^{N}{}_{k=1} \mu_{kik}(x_k)$$
$$i_1, i2... \; i_N = 1, 2...M$$

The 4th layer: The layer has the same junction spots as the third layer and each junction spot has auto adapting function, the output of layer as following:

$$O^{(4)}_{i1i2...iN} = O^{(3)}_{i1i2...iN} \, y_{i1i2...,iN} \quad i_1, i_2, .. \; i_N = 1,2,..M$$

Where $p_{i1i2...iN}^{(k)}$ and $q_{i1i2...iN'}$ are adjustable parameters.

The 5th layer: This layer has only one junction spot, the output of this layer as following:

$$y = O^{(5)} = {}_{i1i2...iN=1}{}^{M} O^{(4)}_{i1i2...iN}$$

ANFIS is a special neural network, if input variables are divided into enough fuzzy sets, the network can accurately approach all kinds of nonlinear function by adjusting parameter of membership function in the first layer and adjusting output function parameter $p_{i1i2...iN}^{(k)}$ and $q_{i1i2...iN'}$. in the fourth layer.

PROPOSED ALGORITHM

The algorithm depends on utilizing WT for its powerful analyzing and decomposing features (David and Octavia, 1996). For five decomposition levels of faulty phase current, std deviation, range are taken as featured input vector for ANFIS. Extracted features may be of anything like maximum, mean, minimum, absolute mean deviation etc. Output vector of ANFIS reveals the type of fault. If the disturbance is classified as a fault on the line the circuit breaker of the line will be tripped. In this proposed scheme, ANFIS is trained with Ia, b and c fault current data taken at different distance of the line. Fault current data are considered for 0.25 cycles from the instant of fault. Features extracted from WT are standard deviations and mean. These are extracted for five decomposition levels of faulty current waveform. Therefore, input vector of ANFIS has 30 variables and its output vector has 1 variable which is normalized in Table 1.

The flowchart of this scheme is shown in Fig. 4.

Table: 1 Meaning of output vector of ANFIS-I

Output vector	Type of fault
1/8	ABCG
2/8	ABG
3/8	BCG
4/8	CAG
5/8	AG
6/8	BG
7/8	CG
8/8	No fault

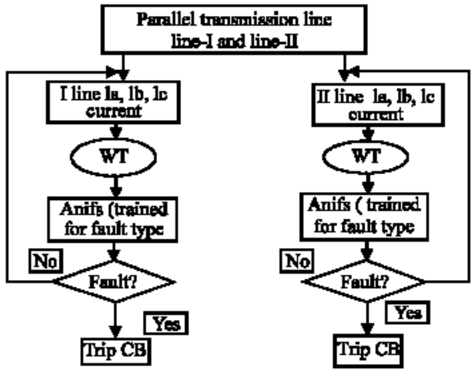

Fig. 4: Flowchart of proposed algorithm

RESULTS AND DISCUSSION

The model network shown in Fig.1 has been simulated using MATLAB. The network consists of two areas connected by two parallel 230 kv transmission lines. Each of the lines has the following specified data as in Table 2. Training data for the ANFIS are prepared by simulating various faults on the line at different distances. For the given system 61 data are prepared from simulation result of various faults with distance of 33km for transmission line.

To ensure the isolation of the faulty line, relay is provided at any one end of the line. Three line currents of two lines are passed through sampling circuits. These sampled signals perform as the inputs to the WT based fault diagnosis algorithm. The described WT-ANFIS algorithm is applied and tested on the model network. The test include ground faults like 3 phase LLLG, SLG, LLG and no fault case at different locations under loading conditions. The fault current for 3phase short circuit fault at 5 km from one end of the Line-I from phase A is recorded as shown in Fig. 5.

This current is then loaded to Wavelet Tool of MATLAB and analyzed with dmey wavelet with five level decomposition. Output of this tool is shown in Fig. 6. And statistics are recorded for each level of decomposition, as shown in Fig. 7. Extracted features of STD deviation range for all levels are arranged to form input vector for ANFIS.

With the proposed procedure, 33KM Parallel line system has been tested and giving 100% performance with only one feature of maximum of two levels of each of phase currents. Therefore, input vector will have 6 components. Similar procedure can be followed for phase currents of the parallel line 2. So CB will be operated according to the decision made by ANFIS. The same proposed procedure has been tested on 220km Parallel line system. It is giving result performance of only 96%.

Table:2 Passive parameters for 230KV transmission line

	Values of		
Parameter	Resistance Ohms km^{-1}	Inductance H km^{-1}	Capacitance F km^{-1}
Positive sequence	0.0529	0.0014	0.0012
Zero sequence	1.61	0.0061	5.2489e-009
Mutual zero sequence	0	0.0002	-1.0000e-012

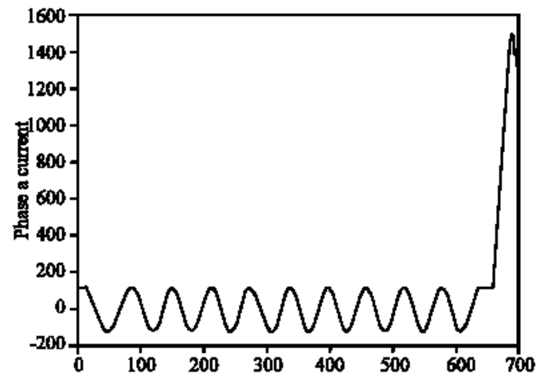

Fig. 5: Fault current from phase A of line-I

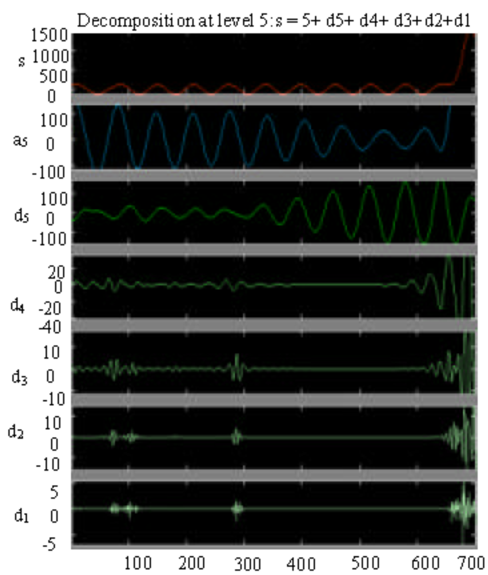

Fig. 6: Five level decomposition of fault current using WT

As the distance of the parallel transmission Line increases, no of training data increases. So performance of ANFIS decreases.

The ANFIS structure for 33 km line is given in Fig. 8. And after completion of training, Error Vs Epochs of the system is shown in Fig. 9.

Test results for various fault simulated at different distances of 33 KM line of the sample system using the proposed algorithm are shown in Fig. 10-13.

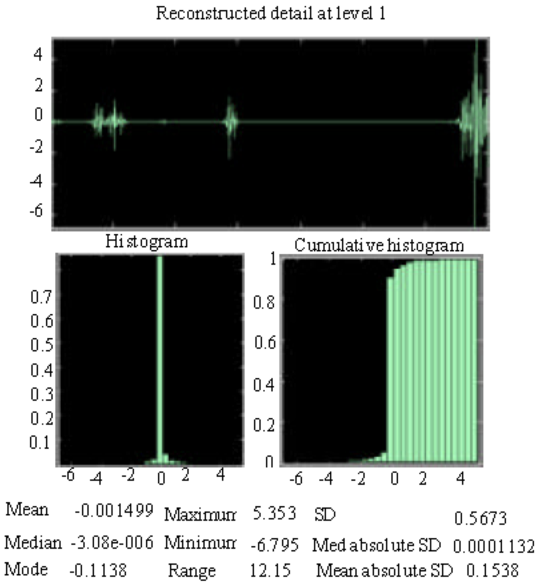

Fig. 7: Statistics of I-level decomposition

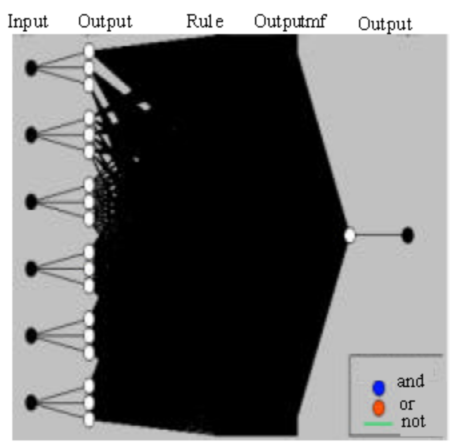

Fig. 8: ANFIS model structure

Training error for fault diagnosis of 33KM Line of sample network with all the input data for an ANFIS is shown in Fig. 9.

Figure10 shows output of ANFIS for ABG fault of Transmission Line 1. Here the actual output of ANFIS should be 0.25 where it indicates 2/8 component of output vector specified in Table1, meaning that Line is with ABG Fault. But ANFIS gives 0.245 as output. Its average testing error is 0.0049194.

Figure 11 shows output of ANFIS for ABCG fault of Transmission Line 1. Here the actual output of ANFIS should b e 0.125 where it indicates 1/8 component of output vector specified in Table 1,

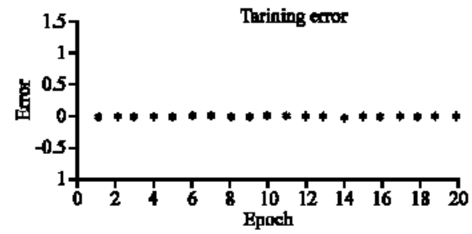

Fig. 9: Error vs epochs of trained ANFIS

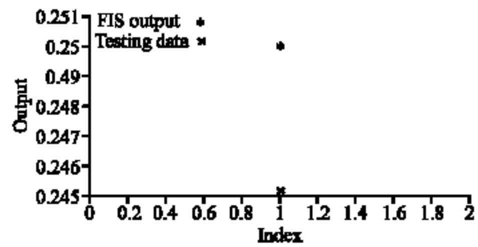

Fig. 10: Output of ANFIS for LLG fault

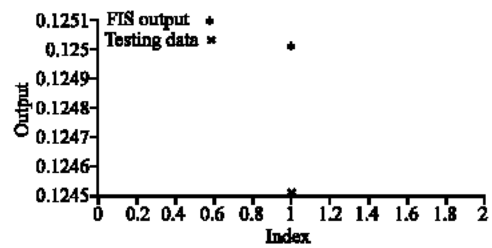

Fig. 11: Output of ANFIS for LLLG fault

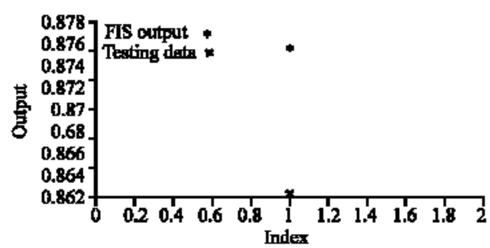

Fig. 12: Output of ANFIS for SLG fault

meaning that Line is with ABG fault. But ANFIS gives 0.1245 as output. Its average testing error is 0.00049169.

Figure 12 shows output of ANFIS for CG fault of Transmission Line1. Here the actual output of ANFIS should be 0.875 where it indicates 7/8 component of output vector specified in Table 1, meaning that Line is with ABG Fault. But ANFIS gives 0.862736 as output. Its average testing error is 0.012264.

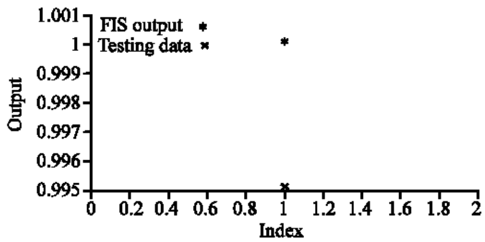

Fig. 13: Output of ANFIS for no fault

Figure 13 shows output of ANFIS for CG fault of Transmission Line1. Here the actual output of ANFIS should be 1 where it indicates 8/8 component of output vector specified in Table1, meaning that Line is with No Fault. But ANFIS gives 0.9952601 as output. Its average testing error is 0.0047399.

CONCLUSION

A new scheme for fault diagnosis of parallel lines is presented in this study. The scheme depends on measuring three phase currents of the parallel lines. The WT with its magnificent characteristics is employed to detect the disturbances in the current signals. The proposed algorithm has been applied for the sample transmission system with length of 33 and 220 km. This algorithm is working with efficiency of 100%. All faults at different locations and loading can be identified in less than half cycle after the fault inception.

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REFERENCES

Osman, A.H. and O.P. Malik, 2004. Protection of Parallel Transmission Lines Using Wavelet Transform. IEEE Transactions on Power Delivery, Vol.19.

Fernando, H. Magnago and Ali Abur, 1998. Fault Location Using Wavelets. IEEE Transactions on Power Delivery, Vol. 13.

Heydt, G.T. and A.W. Galli, 1997. Transient Power Quality Problems Analyzed using Wavelets. IEEE Transactions on Power Delivery, Vol. 12.

David C. Robertson and Octavia I. Camps, 1996. Wavelets and Electromagnetic Power System Transients. IEEE Transactions on Power Delivery, Vol. 11.

Wai, D. and X. Yibin, 1998. A novel technique for high impedance fault identification. IEEE. Trans. Power Delivery, 13: 738-744.

Robertson, D.C., O.I. Campus J.S. Meyer and W.B. Gish, 1996. Wavelet and electromagnetic power system transients. IEEE Trans. Power Delivery, 11: 1050-1056.

Hongkyun Kim, Jinmok Lee, Jae Choi, Sanghoon Lee and Jaesig Kim, 2004. Power Quality Monitoring system Using Wavelet based Neural Network, Int. Conf. Power Sys. Tech. POWERCON, Singapore, pp: 21-24.

Zhixiang Hai, Quntaishen and Heqiinghi, 2003. Nonlinear System Identification Based on ANFIS", IEEE International Conference Neural Networks and Signal Processing, Nanjing, China.