

Detection and Classification of Faults on Parallel Transmission Lines using Wavelet Transform and Neural Network

V.S.Kale, S.R.Bhide, P.P.Bedekar and G.V.K.Mohan

Abstract—The protection of parallel transmission lines has been a challenging task due to mutual coupling between the adjacent circuits of the line. This paper presents a novel scheme for detection and classification of faults on parallel transmission lines. The proposed approach uses combination of wavelet transform and neural network, to solve the problem. While wavelet transform is a powerful mathematical tool which can be employed as a fast and very effective means of analyzing power system transient signals, artificial neural network has a ability to classify non-linear relationship between measured signals by identifying different patterns of the associated signals. The proposed algorithm consists of time-frequency analysis of fault generated transients using wavelet transform, followed by pattern recognition using artificial neural network to identify the type of the fault. MATLAB/Simulink is used to generate fault signals and verify the correctness of the algorithm. The adaptive discrimination scheme is tested by simulating different types of fault and varying fault resistance, fault location and fault inception time, on a given power system model. The simulation results show that the proposed scheme for fault diagnosis is able to classify all the faults on the parallel transmission line rapidly and correctly.

Keywords—Artificial neural network, fault detection and classification, parallel transmission lines, wavelet transform.

I. INTRODUCTION

DOUBLE circuit transmission line or parallel transmission lines have been extensively utilized in modern power systems to enhance the power transfer, reliability and security for the transmission of electrical energy. The different possible configurations of parallel lines combined with the effect of mutual coupling make their protection a challenging problem.

Fundamental part of the digital distance relay is selector module which differentiates between different fault types on

the transmission lines. The selector module should make an accurate decision in less than 10ms to obtain the trip signal quickly. Accurate and fast classification of transmission line faults is also needed for single pole tripping and auto-reclosing.

Application areas of the wavelet transform in power systems include power quality, power system protection, power system transients, partial discharge, transformer protection and condition monitoring. However, power system protection continues to be the major application areas of wavelet transform in power systems [1]. Reference [2] gives an extensive survey of the application of artificial neural network to the problems in the area of power system protection such as transmission line protection, power transformer protection, detection of high impedance faults etc. An algorithm of fault classification and faulted phase selection for a single circuit transmission line based on the initial current traveling wave is very recently proposed in [3]. Identification of simultaneous faults on transmission system using wavelet transform was proposed in [4]. However, authors have reported that further improvement in their proposed algorithm was needed to achieve the desired accuracy. A fault classification scheme based on fuzzy logic has been presented in [5] to identify different faults on transmission line, utilizing full cycle discrete Fourier transform to compute the fundamental components of current signals. Reference [6] shows an application of artificial neural network approach to fault classification for double circuit transmission lines using superimposed sequence components of current signals. Comparison of the Fourier Transform method with Wavelet Transform method for detection and classification of faults on transmission lines was done in [7]. But the authors have reported that wavelet transform based approach gave better results only when more than one phase was involved in the fault. It may be noted that majority of the faults are ground faults that involve only one of the phase conductors and ground. Neural network based double end fed transmission line for faulty phase selection and fault distance location is presented in [8]. Application of artificial neural network for classification of only ground faults on the double circuit transmission line is discussed in [9].

A different approach is adopted here for detection and classification of all ten types of faults which might occur on the individual circuits of the double circuit transmission line. Line currents at the relay locations consist of transients of non-periodic nature significantly when the fault occurs on the

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transmission lines and hence were utilized for the wavelet analysis. The proposed method includes processing of the raw samples of current signals by the discrete wavelet transform, which extracts the embedded fault features. This information is then fed to neural network which classifies the fault. MATLAB technical computing platform was used for offline simulation of various power system network conditions. Multi-resolution analysis method of wavelet analysis and a feed-forward neural network based on the supervised back-propagation learning algorithm were used to implement the proposed fault classification scheme. Neural network was trained with a large number of simulation cases by considering various fault conditions (fault types, fault locations, fault resistances and fault inception angles) for a selected power system network model. It is shown that the proposed algorithm implements a high speed faulty phase selection scheme which operates correctly in variety of situations.

A. Discrete Wavelet Transform

Discrete Wavelet Transform is found to be useful in analyzing transient phenomenon such as that associated with faults on the transmission lines. Multi-Resolution Analysis (MRA) is one of the tools of Discrete Wavelet Transform (DWT), which decomposes original, typically non-stationary signal into low frequency signals called approximations and high frequency signals called details, with different levels or scales of resolution. It uses a prototype function called mother wavelet for this. At each level, approximation signal is obtained by convolving signal with low pass filter followed by dyadic decimation, whereas detail signal is obtained by convolving signal with high pass filter followed by dyadic decimation. The decomposition tree is shown in Fig. 1.

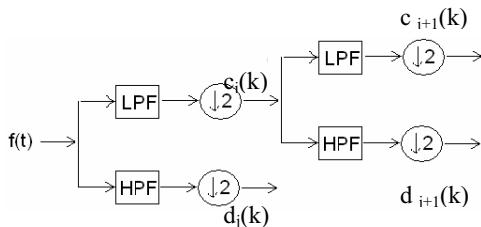


Fig. 1 Decomposition Tree

The DWT maps the one dimensional time domain signal $f(t)$ into two dimensional signal as:

$$f(t) = \sum_k c_j(k) \phi(t - k) + \sum_k \sum_j d_j(k) \psi(2^{-j}t - k) \quad (1)$$

Where c_j , d_j are approximate and detail coefficient respectively; $\phi(t)$ and $\psi(t)$ are scaling and wavelet functions respectively and j is the decomposition level.

B. Neural Network

The feasibility of using artificial neural network (ANN) for transmission line protection has been confirmed. ANN consists of highly distributed interconnections of non linear processing elements and can be considered as an adaptable system that can learn relationships through repeated presentation of data, and is capable of generalizing to new, previously unseen data. Neural networks are used for both regression and classification. In regression, the outputs represent some desired, continuously valued transformation of the input patterns. In classification, the objective is to assign the input patterns to one of several categories. ANNs possess excellent features such as generalization capability, noise immunity, robustness and fault tolerance. Therefore, the decisions made by ANN based relaying algorithm will not be seriously affected by variations in system conditions. For this, neural network for a particular application must be trained. There are different training algorithms for feed-forward networks. All of these algorithms use the gradient of the performance function to determine how to adjust the weights to minimize performance function. The gradient is determined using a technique called back propagation, which involves performing computations backwards through the network.

A variation of back propagation algorithm, called Levenberg-Marquardt (LM) algorithm was used for neural network training, since this algorithm is one of the fastest methods for training moderate-sized feed forward neural networks. It also has a very efficient MATLAB implementation [10]. The LM algorithm to update weights is expressed as:

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \quad (2)$$

Where J is the Jacobian matrix that contains first derivatives of network errors with respect to the weights and biases, e is a vector of network errors, $J^T J$ is an approximation of Hessian matrix, the gradient is $J^T e$ and μ is a scalar affecting the performance function.

II. POWER SYSTEM MODEL

The single line diagram of the double end fed power system under study is shown in Fig.2. SimPowerSystem blockset of Simulink is used for detailed modeling of power system network and fault simulation. A 220 KV, 100 Km double circuit Transmission line is selected for fault simulation and algorithm testing. Short circuit capacity of the equivalent Thevenin sources on two sides of the line is considered to be 1.25GVA. Source to line impedance ratio is 0.5 and X/R ratio is 10. The transmission line is simulated using distributed parameter model. Transmission line parameters are given in Table-I.

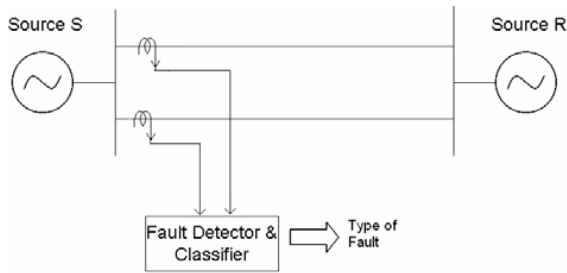


Fig. 2 Power System model under study

TABLE I
DOUBLE CIRCUIT LINE PARAMETERS

Positive sequence resistance R_1 , Ω/KM	0.01809
Zero sequence resistance R_0 , Ω/KM	0.2188
Zero sequence mutual resistance R_{0m} , Ω/KM	0.20052
Positive sequence inductance L_1 , H/KM	0.00092974
Zero sequence inductance L_0 , H/KM	0.0032829
Zero sequence mutual inductance L_{0m} , H/KM	0.0020802
Positive sequence capacitance C_1 , F/KM	1.2571e-008
Zero sequence capacitance C_0 , F/KM	7.8555e-009
Zero sequence mutual capacitance C_{0m} , F/KM	-2.0444e-009

Fig. 3 shows the current waveforms obtained for different faults at a distance of 75 Km from relay location with fault inception angle of 45° and fault resistance of 90Ω .

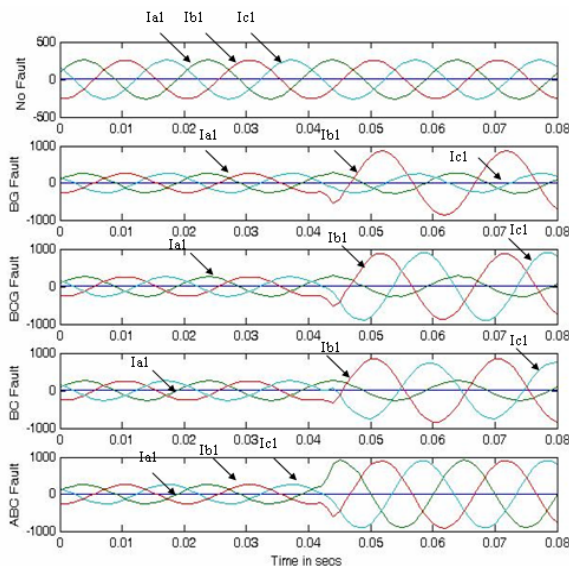


Fig. 3 Simulated line current signals measured at relay location for different types of faults

III. ALGORITHM FOR FAULT DETECTION AND CLASSIFICATION

A. Design Process

The design process of the proposed fault detection and classification algorithm for parallel transmission lines goes through the following steps:

- 1) Formulation of problem, data collection and preprocessing of data using discrete wavelet transform.
- 2) Selection of a suitable ANN topology & structure for a given application.
- 3) Training of ANN and validation of the trained ANN using test patterns to check its correctness in generalization.

Typically training data set is large and representative, comprising of all possible cases that the ANN needs to learn. Combinations of different fault conditions are to be considered and training patterns are required to be generated by simulating different kinds of faults on the power system. Therefore, fault type, fault location, fault resistance and fault inception time are changed to generate the training patterns covering a wide range of different power system conditions as shown below in Table II. During training, the input and desired target are repeatedly presented to the network. As the network learns, the error decreases towards zero. The simulated training data set was used to train the ANN-based relays.

TABLE II
GENERATION OF TRAINING PATTERNS

Type of Fault	LG, LL, LLG, LLL
Fault Location (km)	10,20,30,40,50,60,70,80,90,
Fault Inception Angle	0° to 180°
Fault Resistance (Ω)	upto 50Ω

B. Design of Fault Classifier

The proposed fault classifier scheme is schematically drawn in Fig. 4. It consists of two modules, viz. pre-processing module based on DWT and fault classification module based on ANN. The aim of the pre-processing module is to extract the distinctive features of the input signals, with the purpose of reducing the ANN structure and training process and improving the performance.

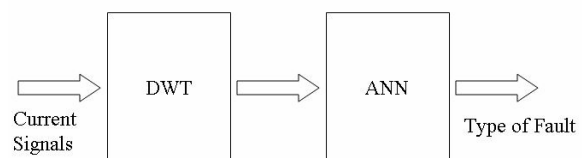


Fig. 4 Fault Detection and Classification Scheme

Three line currents from one of the parallel lines and three line currents from the remaining line are measured at the relay

locations. The sampling frequency used was 12.5 KHz. The Deubechies 8 wavelet is used for analyzing the signals. The sixth decomposition level consists of second and third order harmonic components which are most prominent in the post fault current signals. Therefore, detail coefficients corresponding to this level are manipulated to obtain various parameters which are effectively used as inputs to the neural network. Let, S_{da} , S_{db} , S_{dc} represent sums of sixth level detail coefficients of line currents I_a , I_b and I_c respectively. Similarly Q_{da} , Q_{db} and Q_{dc} represent sums of absolute values of sixth level detail coefficients of line currents I_a , I_b and I_c respectively. After observing the variations of these parameters with respect to fault type, fault inception angle and fault locations, the inputs to the ANN are chosen as absolute sum of S_{da} , S_{db} and S_{dc} as one input, and other inputs are Q_{da} , Q_{db} and Q_{dc} . Thus for the parallel lines total inputs are eight. The ANN output consists of 7 neurons. Seven outputs of the scheme corresponding to phases A1, B1, C1 of one of the parallel transmission lines, phases A2, B2, C2 of the other line and neutral N of the system. Based on the fault type that might occur on the system, each of the network outputs should be either 0 or 1.

The major issue in the design of ANN architecture is to ensure that when choosing the number of hidden layers and number of neurons in the hidden layers, its attribute for generalization is well maintained. In this respect, since there is no parametric/theoretic guidance available, the design has to be based on a heuristic approach [11]. The selected structure of the ANN unit is shown in Fig.5. Hyperbolic tangent function was used as activation function for the neurons in the hidden layers. Pure linear function was the activation function for the neurons of the output layer.

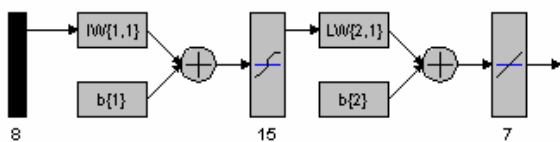


Fig. 5 Neural Network Structure

C. Training With Levenberg-Marquardt Algorithm

Fig. 6 shows the training figure obtained with the LM algorithm while training the neural network, of the proposed fault identifier scheme. As can be seen, the error rapidly converges to the desired level and the training has stopped after 99 iterations, after reaching the set goal of $1e-06$.

The performance of a trained network can be measured to some extent by the errors on the training, validation and test sets, but it is often useful to investigate the network response in more detail. One option is to perform a regression analysis between the network response and the corresponding targets. The fig.7 and fig.8 shows only two of the seven graphical outputs provided by regression analysis. The network outputs viz. 'C1' and 'N' are plotted versus the targets as open circles. The best linear fit is indicated by a dashed line. The perfect fit is indicated by the solid line. From the figures, it is difficult to

distinguish the best linear fit line from the perfect fit line, because the fit is good.

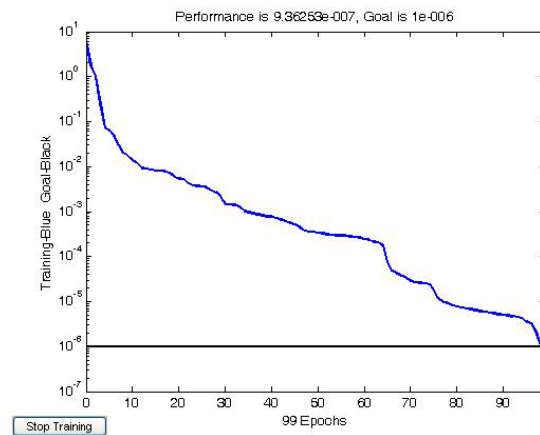


Fig. 6 Training figure for fault classifier

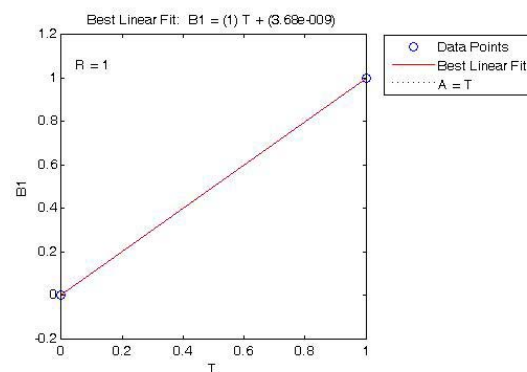


Fig. 7 Regression analysis of output 'B1'

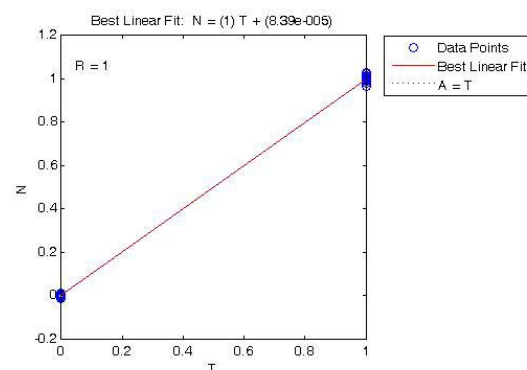


Fig. 8 Regression analysis of output 'N'

IV. TEST RESULTS

The designed ANN based fault classifier was extensively tested with inputs that were not used during training phase. A validation data set consisting of different fault types was generated using given power system model consisting of parallel transmission lines. For different faults of the validation set, parameters such as fault location, fault inception angle and fault resistance were changed to investigate the effects of these factors on the performance of the proposed algorithm. The fault classification scheme, as envisaged here needs eight inputs to turn any of the seven outputs 1 or 0 depending on whether a particular phase is present in the fault loop. Once all the eight inputs are latched into the ANN, it propagates the samples forward through neurons and connecting weights. The propagation delay time from neuron input to neuron output and from layer to layer is negligible as compared to the time required to generate the inputs. Thus, the operating time of the scheme is basically the time required to acquire the preprocessed inputs. It is found that, the proposed classifier scheme classifies the faults with

accuracy and speed. The results of the proposed relay algorithm for few faults with different system conditions are presented in Table III.

V. CONCLUSIONS

In this paper, an accurate technique of automation of identification of faults on parallel transmission lines has been proposed. The method depends on the current signals extracted from the local relay location. Wavelet Transform was used to extract distinctive features in the input signals. This feature vector then acts as input to the neural network improving its speed and accuracy. Capabilities of neural network in pattern classification were utilized. Simulation studies were performed and the performance of the scheme with different system parameters and conditions was investigated. The proposed algorithm was found to be immune to the effect of mutual coupling, fault resistance, remote end infeed, fault location and fault inception angle. Though the paper deals with fault classification but can be extended to the other power system protection problems such as finding fault location.

TABLE III
TEST RESULTS OF FAULT DETECTOR AND CLASSIFIER

Fault Type	Fault Location (km)	Fault Inception Angle, Φ (in deg.)	Fault Resistance, $R_f (\Omega)$	WT & ANN based Fault detector and Classifier Output						
				A1	B1	C1	A2	B2	C2	N
A1G	12	90	40	1.0001	-0.0001	0	0	-0.0001	-0.0001	0.9989
B2C2G	23	60	30	0.0001	0	0	0	1.0000	1.0000	1.0005
A1C1	34	45	0	1.0000	-0.0001	1.0000	0	0	0	0.0061
B2G	45	30	10	-0.0001	-0.0001	0	-0.0002	1.0000	0	0.9998
A2B2	56	0	20	0.0001	0	0	1.0000	1.0000	0	0.0016
A1B1C1	67	45	0	1.0000	1.0000	1.0000	-0.0001	0	0	0.0011
A1B1G	78	90	50	1.0000	1.0000	0	0	0	0	1.0002
C1G	82	30	5	0.0002	-0.0001	1.0001	0	0	-0.0001	0.9983
B2C2	88	60	0	-0.0001	-0.0001	0	-0.0001	1.0000	1.0000	-0.0006
A2C2G	90	0	25	-0.0001	0	0	1.0001	0	1.0000	0.9994
A2B2C2	62	45	0	-0.0002	0	0	1.0000	1.0000	1.0000	-0.0022
B1G	29	90	45	0	1.0000	0	-0.0001	-0.0001	0	1.0002

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