ANN based Fault Detection and Classification of Double Circuit Transmission Line using only One Terminal Data

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ABSTRACT

An accurate fault detection and classification algorithm based on application of artificial neural networks (ANN) for protection of double circuit transmission lines is presented in this research paper. The proposed method uses the magnitude and phase angle of current available at only the local end of line. This method is adaptive to the variation of fault resistance, fault inception angle and fault location. The Simulation results show that all types of phase-to-phase and phase-to-ground faults can be correctly detected and classified under varying system conditions. Large numbers of fault simulations using MATLAB/Simulink software has proved the accuracy and effectiveness of the proposed algorithm.

KEYWORDS: Fault detection (FD), Fault classification (FC), Double circuit transmission line, Artificial neural networks (ANN).

INTRODUCTION

Double circuit transmission lines increase the power transmission capability and reliability of the power system hence it is most widely used. Fault detection and fault classification play a very crucial role in the protection of a double circuit transmission line. However, there is difficulty in fault classification in double circuit transmission line using conventional techniques, mainly because a faulted phase(s) on one circuit has an effect on the phases of the healthy circuit due to mutual coupling effect between the two circuits. Hence it is difficult to discriminate between the faulty line and healthy line especially in the case of faults near the remote end bus. The speed and accuracy of digital distance relaying protection schemes can be improved by accurate and fast phase selection and this also allows single-phase tripping schemes to be employed for protection of doubt circuit transmission lines. Well-developed protective algorithm should perform well for different system conditions and parameters such as fault resistance, fault inception angle, fault location etc.

Various kinds of fault detection and fault classification techniques were proposed in the literature. The majority of these techniques are based on the magnitude of sampled voltage and current signals at the relay location. Recently, the modern technologies of protection relay are mainly based on the application of artificial intelligence tools like fuzzy logic (FL), artificial neural networks (ANN) and adaptative network-based fuzzy inference system (ANFIS) techniques which are promising alternatives compared with the conventional techniques. ANN has excellent features such as the robustness, immunity to noise and the fault-tolerance. Therefore, the decision made by an ANN based relay will not be seriously affected by variations in the system parameters such as fault resistance, fault inception angle, fault location etc.

An artificial neural network based fault detection and classification approach was proposed in this paper. The algorithm employs the magnitude and phase angles of current signals of each phase of the two parallel lines at one end only. The protection algorithms proposed were tested by a number of offline tests to investigate its performances in terms of precision and robustness. The protection algorithms proposed are able to detect and classify all types of the faults in a double circuit transmission line using only one terminal data considering the effects of varying fault resistance, fault location, and fault inception angle.

MODELLING OF POWER SYSTEM NETWORK

The power system network studied is composed of 220KV, 50 Hz, 100km double-circuit transmission lines, connected to a source at each end, as shown in Fig. 1. All components of the power system network are modeled by the MATLAB ® Simulink & SimPowerSystem toolbox. The transmission line is simulated using distributed parameter line model. The Short circuit rating of the equivalent Thevenin sources on two sides of the line are considered to be 1.25 GVA with X/R ratio 10 and source to line impedance ratio is 0.5. The double circuit transmission line parameters are shown in Table-1.

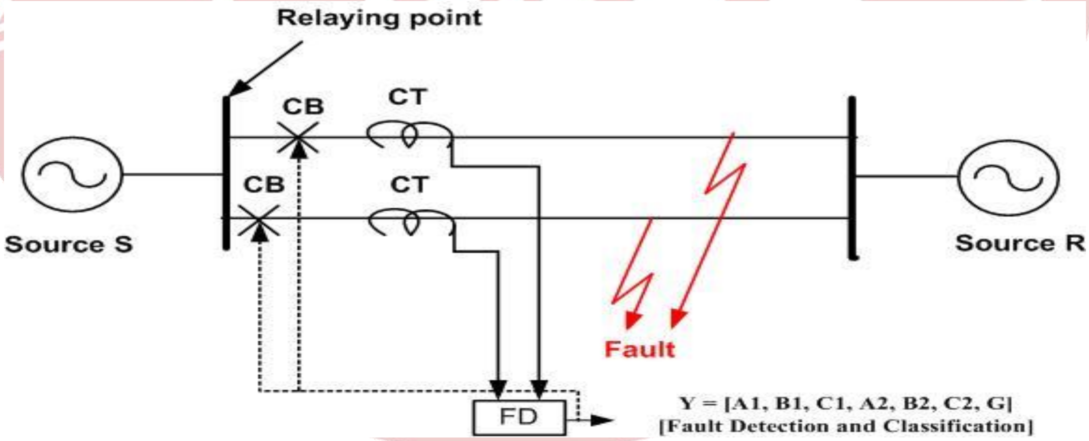
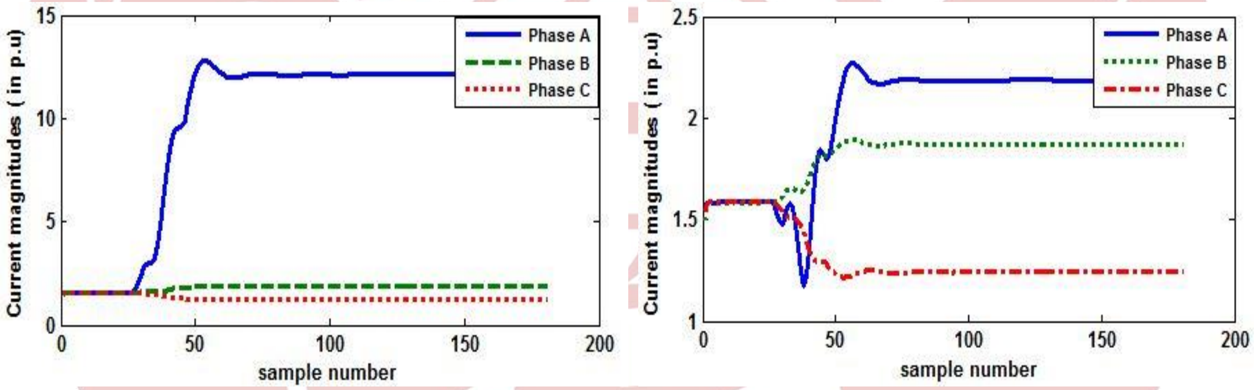


Figure 1: Single line diagram of power system model under study

Components	Parameters	
Transmission line	Length (km)	100
	Voltage (kV)	220
	Positive sequence impedance (Ω/km)	0.0181 + j0.292
	Zero sequence impedance (Ω/km)	0.2188 + j1.031
	Zero sequence mutual impedance (Ω/km)	0.20052 + j0.6535
	Positive sequence capacitance (nF/km)	12.571
	Zero sequence capacitance (nF/km)	7.8555
	Zero sequence mutual capacitance (nF/km)	-2.0444

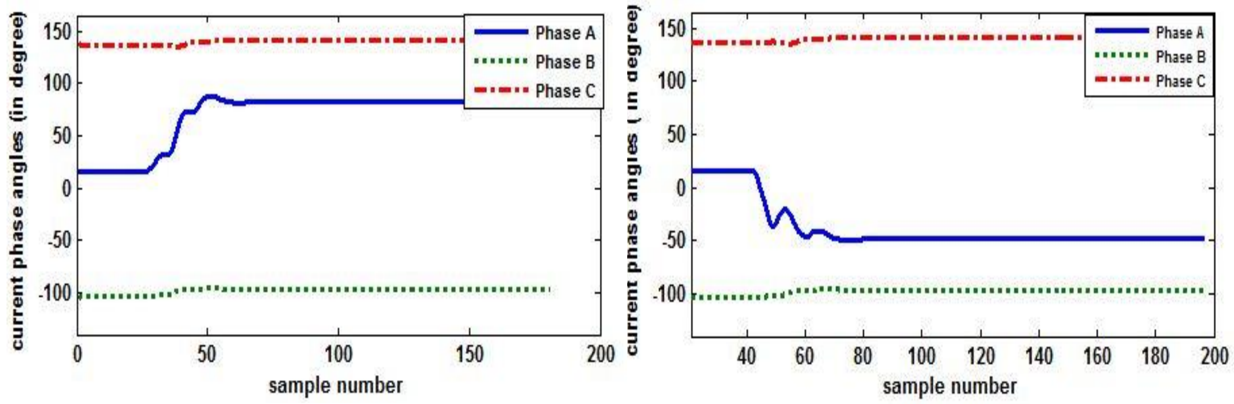
Table 1: Double circuit transmission line parameters

The magnitude and phase angle of current signals changes under the occurrence of the fault. The magnitude and phase angle of each phase current signals of both circuit1 and circuit2 are extracted using Discrete Fourier Transform. The magnitude and phase angle of current signals under the occurrence of A1G fault at 10 km from the sending end bus with fault resistance R_f = 10Ω and at a fault inception angle of $\Phi_i = 90^o$ are shown in Fig. 2(a)(b) and Fig. 3(a)(b).



(a) (b)

Figure 2: (a) Current signal magnitude of faulty circuit-1 (b) Current signal magnitude of healthy circuit-2 under A1G fault at 10 km with R_f = 10Ω, $\Phi_i = 90^o$



(a) (b)

Figure 3: (a) Phase angle of current signals of faulty circuit-1 (b) Phase angle of current signals of healthy circuit-2 under A1G fault at 10 km with $R_F = 10\Omega$, $\Phi_i = 90^o$

It is clear from Figures 2 and 3 that after the occurrence of "A1G" fault there is significant change in magnitude and phase angle of current signals of A1- phase of faulty circuit 1. As expected, there is a change in magnitude and phase angle of current signals of healthy circuit 2 due to the mutual coupling between the two circuits. These changes in phase angles and the magnitude of current signals are used in the proposed method to detect and classify the faults in the present work.

Current signals at relaying point were acquired via current transformer CT. These current signals are preprocessed in order to significantly reduce the size of the neural network and improve the performance and speed of training process. Six current signals are treated using an antialiasing low pass filter to eliminate the frequencies not desired starting from a wave form sampled at a frequency of 1 kHz. Sampling frequency 1 kHz is selected because this sampling rate is compatible with the sampling rates currently used in the digital relays. Subsequently, one full cycle Discrete Fourier transform is used to calculate the magnitude and phase angles of the currents signals. It is advisable to mention that the current samples to be treated must be standardized in order to reach the input level of the ANN (± 1) [15].

STRUCTURE OF THE PROPOSED ANN FOR FAULT DETECTOR AND FAULT CLASSIFICATION

The basic procedure used to implement a neural network for the fault detection and classification algorithm in double circuit transmission line is described below.

A. Selecting the right architecture:

The main factor in determining the right size and structure for the neural network is the number of inputs and outputs that it must have. To enable the method to be implemented in both fault detection and classification, the magnitude and phase angles of each current signals recorded at the relay location are extracted by using discrete Fourier transform and the difference between maximum phase angle and minimum phase angle for each current signals are calculated as given below:

$$\theta_{max} = \max\{\theta(1), \theta(2), \ldots, \theta(m)\} \quad (1)$$

$$\theta_{min} = \min\{\theta(1), \theta(2), \ldots, \theta(m)\} \quad (2)$$

$$\Delta\Phi = \Phi_{max} - \Phi_{min} \quad (3)$$

Where θ_{max} and θ_{min} are the maximum and minimum phase angle out of m samples for current signals of the corresponding phases. Hence the neural network inputs chosen here are the magnitude and changes in the phase angles of six currents measured at the relay location. As the basic task of the fault detector is to detect whether fault has occurred or not, hence neural network provides only one output either '0' or '1' where '0' represents no fault case and '1' represents faulty case. Thus the input **X** and the output **Y** for the fault detection network are:

$$X = [\Delta\Phi A1, \Delta\Phi_{B1}, \Delta\Phi_{C1}, \Delta\Phi_{A2}, \Delta\Phi_{B2}, \Delta\Phi_{C2}, I_{A1}, I_{B1}, I_{C1}, I_{A2}, I_{B2}, I_{C2}] \quad (4)$$

$$Y = [\text{Fault (1)-No fault (0)}] \quad (5)$$

Similarly, task of fault classification is to identify the fault type by detecting the faulty phases, hence seven outputs corresponding to six phases and ground are considered here as outputs provided by the neural network for fault classification task. Thus the input vector X and the output vector Y for the fault classification network are given as:

$$X = [\Delta\Phi A1, \Delta\Phi_{B1}, \Delta\Phi_{C1}, \Delta\Phi_{A2}, \Delta\Phi_{B2}, \Delta\Phi_{C2}, I_{A1}, I_{B1}, I_{C1}, I_{A2}, I_{B2}, I_{C2}] \quad (6)$$

$$Y = [A1, B1, C1, A2, B2, C2, G] \quad (7)$$

B. Design process:

After analysis of different neural networks with combinations of activation functions, it was decided to use a four layers neural network with 12 neurons in the input layer, 12 neurons in the first hidden layer and 8 neurons in the second hidden layer and 1 neuron in the output layer (12-12-8-1) for fault detection as shown in Fig. 4. After analyzing various transfer functions 'logsig' transfer function is used for both hidden layer and for output layer 'purelin' transfer function was used.

Similarly, for fault classification task a five layers neural network with 12 neurons in the input layer, 24 neurons in the first hidden layer, 18 neurons in the second hidden layer, 12 neurons in the third hidden layer and 7 neuron in the output layer (12-24-18-12-7) was used as shown in Fig. 4. After analyzing various transfer functions 'tansig' transfer function is used for all hidden layers and for output layer 'purelin' transfer function was used.

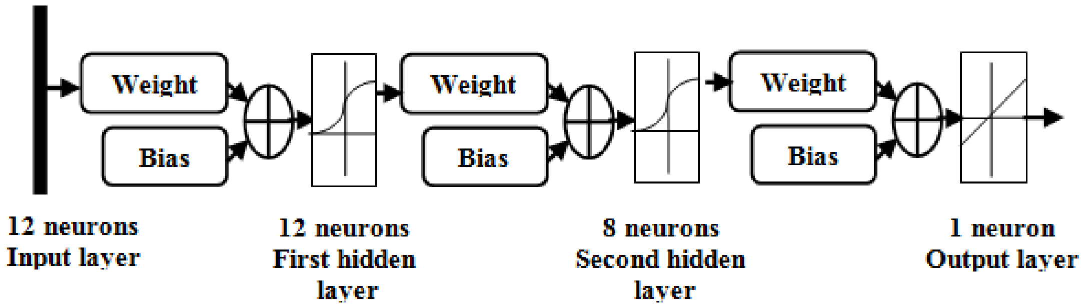


Figure 4: Architecture of ANN Based Fault Detector

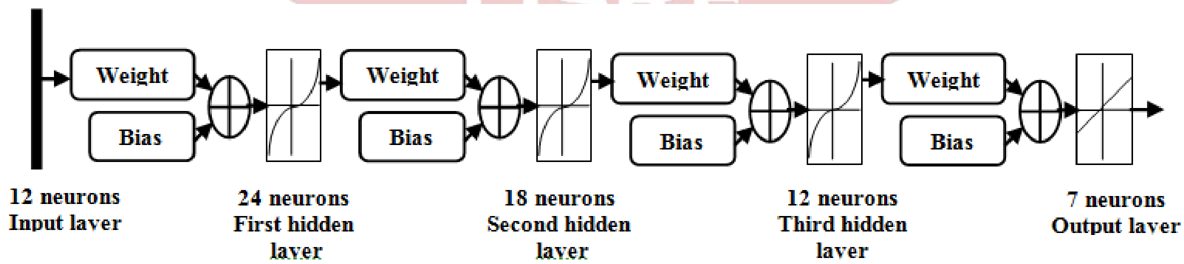


Figure 5: Architecture of ANN Based Fault Classification

C. Training process:

To train the neural network, it is necessary to select a suitable number of representative examples of the relevant phenomenon so that the network can learn the fundamental characteristics of the problem and, once training is completed, provide correct outputs in new situations that have not been used during training process. Using SIMULINK & SIMPOWERSYSTEM toolbox of MATLAB each type of phase faults and ground faults at different fault locations between 0-100% of line length, fault inception angles and different fault resistance have been simulated as shown in Table 2.

Parameters	Set Value
Type of Faults	A1-G, B1-G, C1-G, A1-B1, B1-C1, C1-A1, A1-B1-G, B1-C1-G, C1-A1-G, A1-B1-C1, A1-B1-C1-G A2-G, B2-G, C2-G, A2-B2, B2-C2, C2-A2, A2-B2-G, B2-C2-G, C2-A2-G, A2-B2-C2, A2-B2-C2-G
Fault Location	1, 4, 8, 13, 20, 35, 48, 59, 73, 87, 99
Fault Resistance	1,60,120,180 Ω (for ground fault) & 0 Ω (for phase fault)
Fault Inception Angle	0º & 90º

Table 2: Training Data Pattern Generation

Thus the total numbers of faults simulated for phase faults are 8 x 11 x 1 x 2= 176 and the total numbers of faults simulated for ground faults are 14 x 11 x 4 x 2= 1232. Thus the total number of patterns generated for training is 1408(fault case) +1(no fault case) =1409 for the fault detection task and 1408 for fault classification task. Both the networks for fault detection and fault classification were trained using Levenberg– Marquardt training algorithm using neural network toolbox of MATLAB®7.10. This learning strategy converges quickly and the mean squared error (mse) decreases in 229 epochs to 9.91e-12 for fault detection task as shown in figure 6 and for fault classification task the mse decreases in 1877 epochs to 8.58e-05 as shown in figure 7.

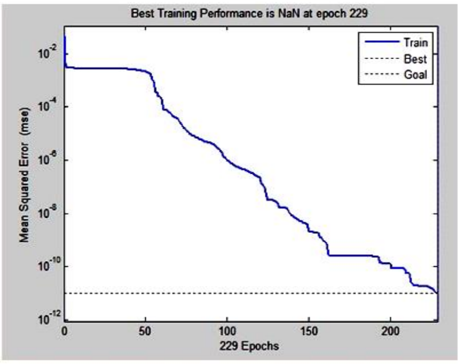


Figure 6: Mean-square error performance of network for fault detector

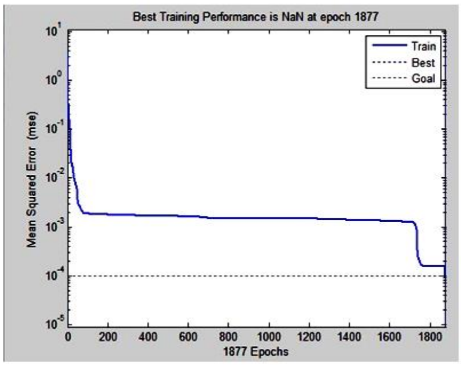


Figure 7: Mean-square error performance of network for fault classification

TEST RESULTS OF ANN BASED FAULT DETECTOR AND FAULT CLASSIFIER

To investigate the effect of system parameters such as fault resistance, fault inception angle and fault location on the performance of the proposed ANN based protection scheme test data set was generated for all types of faults by varying all system parameters. The network was tested and validated by presenting different fault cases with varying fault resistance R_f (0-175 Ω), fault locations L_f (0-99 km) and fault inception angles Φi (0-360°). ANN based Fault Detector & Classifier test results are shown in table 3, it clearly states the all the faults cases are correctly detected and classified. This confirms well the effectiveness of the fault detector and fault classifier proposed for the protection of double circuit transmission line.

Fault Type	Fault Resist-ance R_f (ohm)	Fault inception angle Φi (deg)	Fault Location L_f (in km)	FD Output	FC Output						
					A1	B1	C1	A2	B2	C2	G
A1G	3	0	3	1	1.00	0.00	0.00	0.00	0.00	0.00	1.00
C2G	45	60	25	1	0.00	0.00	0.00	0.00	0.00	1.00	0.99
B1G	68	135	98	1	0.00	1.00	0.00	0.00	0.00	0.00	0.99
A1B1G	97	225	46	1	0.99	0.99	0.00	0.00	0.00	0.00	1.00
A2C2G	123	270	53	1	0.00	0.00	0.00	1.00	0.00	1.00	1.00
B1C1G	175	360	67	1	0.00	1.00	1.00	0.00	0.00	0.00	1.00
A1B1	0.01	45	71	1	1.00	0.99	0.00	0.00	0.00	0.00	0.08
A2B2C2	0.01	90	76	1	0.00	0.00	0.00	1.00	0.99	1.00	0.10
A1B1C1G	85	180	89	1	1.00	1.00	0.99	0.00	0.00	0.00	0.99
A2B2C2G	150	60	13	1	0.00	0.00	0.00	1.00	1.00	1.00	1.00

Table 3: ANN based Fault Detector & Classifier test results

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CONCLUSION

This paper presents new approaches for the ANN based fault detection and classification in double circuit transmission line using only one terminal data, which can be used in the digital protection of the double circuit power transmission system. These approaches are based on magnitude and changes in the phase angle of current signals of each phase of both the circuits which is given as input to the corresponding artificial neural network for fault detection and fault classification task. The protection scheme effectively eliminates the effect of varying fault resistance, fault location and fault inception angle. The performance of the proposed protection scheme has been investigated by a number of offline tests considering all possible types of faults with varying fault resistance R_f (0-175 Ω), fault locations L_f (0-99 km) and fault inception angles Φi (0-360°).Test results show that the fault detector and fault classifier proposed can be used to very support a new generation of protection relay systems at high speed. These advantages make the proposed techniques extremely suitable for online and supervised detection and classification of faults with high fidelity in large-scale power systems.

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