# Fault Classification and Faulty Section Identification in Teed Transmission Circuits Using ANN

Prarthana Warlyani, Anamika Jain, A.S.Thoke, *Member IEEE,* and R.N.Patel, *Member IEEE*

***Abstract*—An accurate fault classification algorithm for Teed transmission Circuit based on application of artificial neural networks (ANN) is presented in this paper. The proposed algorithm uses the voltage and current signals of each section measured at one end of teed circuit to detect and classify Double line to ground faults. ANN has the ability to classify the nonlinear relationship between measured signals by identifying different patterns of the associated signals. The adaptive protection scheme based on application of ANN is tested for double line to ground faults, varying fault location, fault resistance and fault inception angle. An improved performance is experienced once the neural network is trained adequately, gives accurate results when faced with different system parameters and conditions. The entire test results clearly show that the fault is detected and classified within one cycle; thus the proposed adaptive protection technique is well suited for teed transmission circuit fault detection and classification. Results of performance studies show that the proposed neural network-based module can improve the performance of conventional fault selection algorithms.**

***Index Terms*—Teed transmission circuit, fault detection, classification, double line to ground faults and artificial neural network.**

## I. Introduction

The protection of multi-terminal lines is not as simple as that of two-terminal lines. They usually experience additional problems caused by the intermediate infeed from the third terminal, or an outfeed to the terminal, difference in line length to tee point and also due to different source impedances [1]. Most of the work reported deals with two terminal lines with less attention to teed feeders transmission line configurations. In [2] the high frequency traveling-wave information contained in the post fault voltage and current signals are used for protection of teed circuits. 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 the fault and the remote end of the line. The wavelet transform analysis [3, 4] is based on the high-frequency components of the fault generated signals on each terminal of the system. The limitation stated is that at low signal-noise ratio (SNR), the method becomes inefficient. In a directional comparison technique [5] the polarity of the fault generated transient current signals is detected at each end of teed circuit and is then sent over to the line remote ends through communication link. A digital differential relaying scheme [6] involves deriving differential signals that are functions of both voltages and currents measured at each end. The scheme is based on master and slave principles using a fibre optic link as a means of communication between ends. Fault Location algorithm for locating unbalanced faults based on negative-sequence quantities from all line terminals for two or three terminal lines is reported in [7]. Fault location schemes using synchronized phasor measurements for multi-terminal transmission line have been developed in [8-10]. There has been a very limited attention to the use of artificial neural network for protection of teed transmission circuit [11]. Eyada et. al [11] use radial basis function neural network for fault distance location in teed circuits and also detects the fault type but the network does not identify the phase in which the fault occurs.

ANN is powerful in pattern recognition, classification and generalization. ANN-based techniques show a great enhancement in the accuracy of fault classification and location in comparison with the conventional techniques. This is due to the features of ANN which do not exist in the conventional methods such as the capability of non-linear mapping, parallel processing, learning and generalisation.

In this work, we present an extension to neural network based transmission line fault detection and classification technique reported in [12] (which addresses double circuit transmission lines), to teed circuit transmission line and propose an adaptive protection scheme for such systems by using the ANN approach. Based on the authors' comprehensive digital simulations of the teed-circuit transmission systems, particular emphasis is placed on data preprocessing for feature extraction used as inputs to the ANN. The pattern classifier, i.e. the protection technique, is tested for LLG (double line to ground faults) under different fault locations, fault resistances, and fault inception angles. A 220 kV teed-circuit line configuration is simulated using MATLAB®-Simpower and Simulink software.

## II. Power System Network Simulation

The system studied is composed of 220 KV Teed transmission circuit with section lengths 200 km (section 1), 120 km (section 2) and 110 km (section 3), connected to sources at each end. The single line diagram of the line is shown in Fig. 1. Short circuit capacity of the equivalent thevenin sources on each sides of the line is considered to be 1.25 GVA and X/R ratio is 10. The transmission line is simulated with distributed parameter line model using MATLAB® software as shown in Fig.2. Teed circuit

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transmission line parameters are shown in Table I.

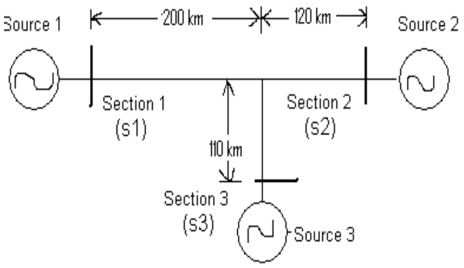



Fig. 1. Single line diagram of power system under study.

TABLE I:TEED CIRCUIT LINE PARAMETER

| | |
|---|---|
| Positive sequence resistance R1, Ω/KM | 0.01809 |
| Zero sequence resistance R0, Ω/KM | 0.2188 |
| Positive sequence inductance L1, H/KM | 0.00092974 |
| Zero sequence inductance L0, H/KM | 0.0032829 |
| Positive sequence capacitance C1, F/KM | 1.2571e-008 |
| Zero sequence capacitance C0, F/KM | 7.8555e-009 |

Preprocessing is a useful method that significantly reduces the size of the neural network and improves the performance and speed of training process [13]. Three phase voltages and three phase current input signals were sampled at a sampling frequency of 1 kHz and further processed by simple 2nd-order low-pass Butterworth filter with cut-off frequency of 400 Hz. Subsequently, one full cycle Discrete Fourier transform is used to calculate the fundamental component of voltages and currents. The input signals were normalized in order to reach the ANN input level (±1).

## III. ANN BASED FAULT DETECTOR AND CLASSIFIER

The various steps used to implement a neural network in the fault detection and classification algorithm in teed circuit transmission line is described below.

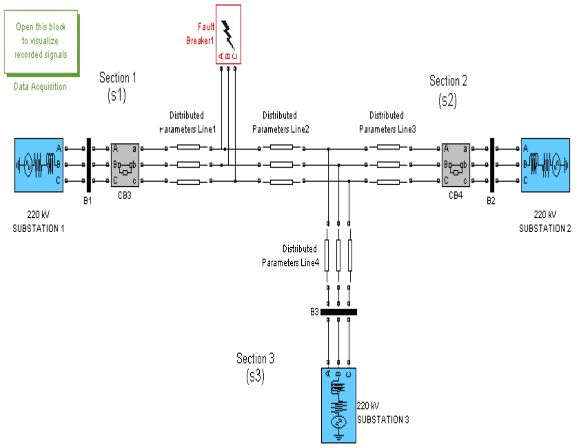



Fig. 2. Power system model simulated in MATLAB Simulink software.

### A. Training Pattern Generation

The training data set of an ANN contains the necessary information to map the input patterns to corresponding output patterns. Using SIMULINK & SimPowerSystem toolbox of MATLAB double line to ground faults (ABG , BCG, CAG for each section) at different fault locations between 0-90% of line length and fault inception angles between 0 & 90° have been simulated as shown below in Table II. The number of fault simulated for double line to ground faults (ABG, BCG and CAG) for each section are 360 (3×20×3×2 for section 1) i.e. (types of fault number of fault locations fault resistances fault inception angles), 216 (3×12×3×2 for section 2) and 198 (3×11×3×2 for section 3). Thus, the total number of fault cases simulated for double phase to ground faults is 774. From each fault case ten numbers of post fault samples have been extracted to form the data set for neural network. 20 samples during no fault are also collected for the fault classification task. Thus, the total number of patterns generated for training is 7760 for the fault classification task.

TABLE II: PATTERNS GENERATION

| S.No. | Parameters | Set values |
|---|---|---|
| 1. | Fault type | ABG,BCG, CAG |
| 2. | Fault location in km | Section 1 - 0,10,20,30,…….190 km<br>Section 2 - 0,10,20,30,……..110 km<br>Section 3 - 0,10,20,30,……..100 km |
| 3. | Fault inception angle | 0° and 90° |
| 4. | Fault resistance | 0,50 and 100 Ω |

### B. Input and Output Selection

One factor in determining the right size and structure for the network is the number of inputs and outputs that it must have. The lower the number of inputs, the smaller the network can be. However, sufficient input data to characterize the problem must be ensured. Hence the network inputs chosen here are the magnitudes of the fundamental components (50 Hz) of three phase voltages and three phase currents of each section measured at one end. As the basic task of fault classification is to determine the type of fault along with the phase, three outputs corresponding to three phases, one output to represent whether neutral is involved in the fault loop and three outputs to represent at which line section fault is present. Thus total seven outputs were considered to be provided by the network for fault classification. The inputs **X** and outputs **Y** for the fault classification network are:

$$X = [Va1,Vb1,Vc1, Ia1, Ib1, Ic1, Va2, Vb2, Vc2, Ia2, Ib2, Ic2, Va3, Vb3, Vc3, Ia3, Ib3, Ic3] \quad (1)$$

$$Y = [A,B,C, G, S1, S2, S3] \quad (2)$$

### C. Structure of ANN Based Fault Classifier

Once it was decided how many input and output the network should have, the number of layers and the number of neurons per layer were considered. The number of neurons in hidden layer is determined empirically by experimenting with various network configurations. Through a series of trials and modifications of the ANN architecture, the best performance was achieved by using a three layer network with 18 neurons in the input layer, 13 neurons in the hidden layer, and 7 neurons in the output layer as shown in Fig. 3. The final determination of the neural network requires the relevant transfer functions in the hidden and output layers to be established. Activation function of the hidden layer is hyperbolic tangent sigmoid function. Neurons with sigmoid function produce real valued outputs that give the ANN ability to construct complicated decision boundaries in an n-dimensional feature space. This is important because the smoothness of the generalization function produced by the neurons, and hence its classification ability, is directly dependent on the nature of the decision boundaries. Saturating linear transfer function (Satlin) has been used in the output layer as shown in Fig. 3. Depending on the fault type which occurs on the system, various outputs of the network should be 0 or 1.

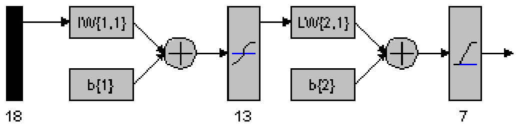



Fig. 3. Structure of ANN based fault detector and classifier

### D. Learning Rule Selection

The back-propagation learning rule is used in perhaps 80–90% of practical applications. Improvement techniques can be used to make back-propagation more reliable and faster. The back-propagation learning rule can be used to adjust the weights and biases of networks to minimize the sum-squared error of the network. This is done by continually changing the values of the network weights and biases in the direction of steepest descent with respect to error. As the simple back-propagation method is slow because it requires small learning rates for stable learning, improvement techniques such as momentum and adaptive learning rate or an alternative method to gradient descent, Levenberg–Marquardt optimisation, can be used. Various techniques were applied to the different network architectures tested, and it was concluded that the most suitable training method for the architecture selected was based on the Levenberg–Marquardt optimization technique.

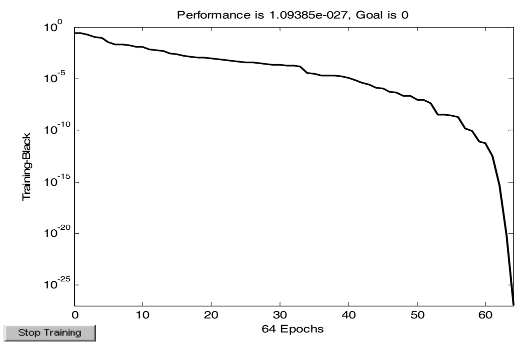



Fig. 4 Training figure obtained with levenberg-marquardt algorithm for ANN based fault detector and classifier.

### E. Training Process

The networks for fault classification and fault distance location were trained using Levenberg–Marquardt training algorithm using neural network toolbox of Matlab [14]. This learning strategy converges quickly and the mean squared error (mse) decreases in 64 epochs to 1.09385e-027 for fault detection and classification task. Fig.4 shows the corresponding RMS error of the ANN based Fault Detector and Classifier with the preprocessed training sets. As, the training is done off line, the iterations and time required for training are not of great concern. The trained network is tested for new cases, not covered in training pattern to demonstrate the viability of the proposed network.

## IV. Test Results of ANN Based Fault Detector and Classifier

ANN based Fault detector and classifier was then extensively tested using independent data sets consisting of fault scenarios never used previously in training. For different faults of the validation/test data set, fault type, fault location and fault inception angle were changed to investigate the effects of these factors on the performance of the proposed algorithm. The network was teste by presenting different double line to ground fault cases with varying fault locations (0-90% of total length) and fault inception angles ($\Phi_i$ =0-360°). As shown in table III all the faults cases are correctly classified. Fig. 5. shows the test results of the ANN based fault detector and classifier for "BCG" fault in section-2 at 50KM, fault inception time at 67.5ms ( $\Phi_i$ = 135°) and fault resistance $R_f$ is 75Ω and Fig. 6 shows the test results of the ANN based fault detector and classifier for sequential fault AG fault at 60ms, 100KM in section 1 with $R_f$=50Ω fault resistance and then switched to ABG fault at 65ms. It is clear from this Fig.5 and Fig.6 that the fault is correctly detected and classified in less than one cycle from the inception of fault.

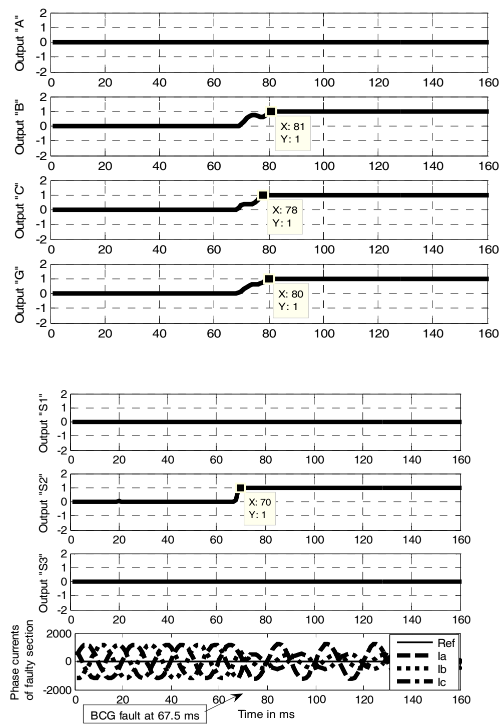
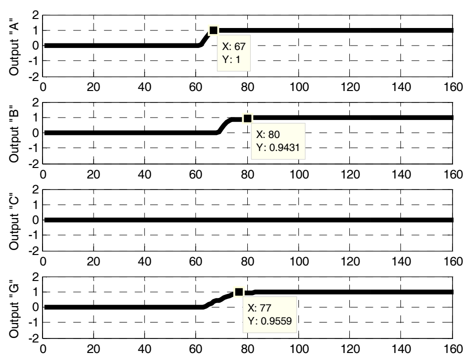



Fig. 5. Test result for BCG fault at 50KM from section 2 at fault inception angle $\Phi_i$ =135°and fault resistance $R_f$=75Ω.



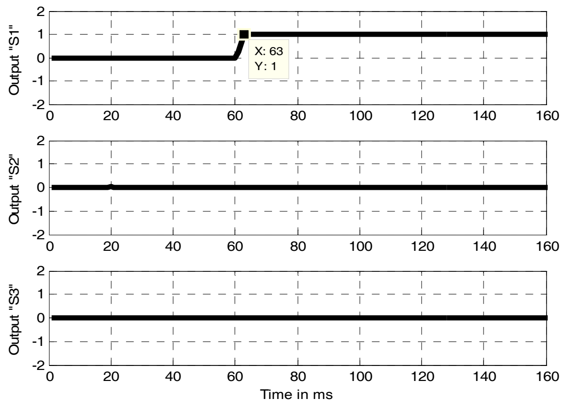



Fig. 6. Test result for sequential faults: AG fault at 60ms, 100KM in section 1 with $R_f$=50Ω fault resistance and then switched to ABG fault at 65ms.

## V. Conclusion

An accurate algorithm based on ANN for fault detection and classification of double line-to-ground faults on teed circuit transmission line fed from sources at each ends is presented. The algorithm employs the fundamental components of three phase voltages and the three phase currents of each section measured at one end ,so it requires less communication. The algorithm provides automatic determination of faulted types and phases after one cycle from the inception of fault. The algorithm effectively eliminates the effect of varying fault location, fault inception angle and fault resistance. The performance of the proposed scheme has been investigated by a number of offline tests. The complexity of the possible types of faults (ABG, BCG, CAG for each section), fault locations (0-90%), fault inception angles (0 & 360°) are solved. The proposed scheme allows the protection engineers to increase the reach setting i.e. greater portion of line length can be protected as compared to earlier techniques.

TABLE III: ANN Based Fault Detector and Classifier Test Results

| Section | Fault type | Fault inception angle in ° | Fault location in KM | Fault resistance in Ω | ANN based fault detector and classifier output | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | A | B | C | G | S1 | S2 | S3 |
| 1 | ABG | 0 | 130 | 75 | 1 | 1 | 0 | 1 | 1 | 0 | 0 |
| | ABG | 90 | 30 | 90 | 1 | 1 | 0 | 1 | 1 | 0 | 0 |
| | BCG | 180 | 50 | 50 | 0 | 1 | 1 | 1 | 1 | 0 | 0 |
| | BCG | 225 | 70 | 45 | 0 | 1 | 1 | 1 | 1 | 0 | 0 |
| | CAG | 270 | 90 | 90 | 1 | 0 | 1 | 1 | 1 | 0 | 0 |
| | CAG | 315 | 110 | 75 | 1 | 0 | 1 | 1 | 1 | 0 | 0 |
| 2 | ABG | 135 | 40 | 75 | 1 | 1 | 0 | 1 | 0 | 1 | 0 |
| | ABG | 45 | 85 | 75 | 1 | 1 | 0 | 1 | 0 | 1 | 0 |
| | BCG | 135 | 50 | 75 | 0 | 1 | 1 | 1 | 0 | 1 | 0 |
| | BCG | 270 | 110 | 90 | 0 | 1 | 1 | 1 | 0 | 1 | 0 |
| | CAG | 315 | 10 | 75 | 1 | 0 | 1 | 1 | 0 | 1 | 0 |
| | CAG | 360 | 70 | 90 | 1 | 0 | 1 | 1 | 0 | 1 | 0 |
| 3 | ABG | 45 | 30 | 75 | 1 | 1 | 0 | 1 | 0 | 0 | 1 |
| | ABG | 180 | 50 | 75 | 1 | 1 | 0 | 1 | 0 | 0 | 1 |
| | BCG | 135 | 10 | 50 | 0 | 1 | 1 | 1 | 0 | 0 | 1 |
| | BCG | 90 | 65 | 45 | 0 | 1 | 1 | 1 | 0 | 0 | 1 |
| | CAG | 270 | 50 | 100 | 1 | 0 | 1 | 1 | 0 | 0 | 1 |
| | CAG | 360 | 70 | 90 | 1 | 0 | 1 | 1 | 0 | 0 | 1 |

## 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.on Power Delivery*", Vol. 8, Jul. 1993, pp. 874-883.

[2] P. G. McLarenm and S. Rajendra, "Travelling wave technique applied to the protection of teed circuits:- principle of traveling – wave technique" *IEEE Trans. on power apparatus and systems*, Vol. PAS-104, No12, December 1985, pp. 3544 - 3550.

[3] 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 Seminar on Time-scale and Time-Frequency Analysis and Applications*, London, Feb. 2000, pp. 15/1 - 15/5.

[4] M. 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 Transmission and Distr. Conf. and Exposition,* Latin America, Venezuela, 2006, pp. 1-6.

[5] P. L. Mao, Z. Q. Bo, L. Z. Yao, R. M. Li, "Protection of teed transmission circuits using A new directional comparison technique," *Proceedings of International Conference on Power System Technology, (POWERCON)*, 18-21 Aug 1998, Vol.2, pp. 1111 – 1115.

[6] R. K. Aggarwal and A. T. Johns, "Digital differential relaying scheme for teed circuits based on voltage and current signal comparison", *IEEE proceedings*, Vol. 137 Pt.C, No.6, November 1990, pp. 414-423.

[7] D. A. Tziouvaras, J. B. Robrts, and G. Benmouyal, "New Multi-ended Fault Location Design for two- or three terminal lines," *Proceedings* of *IEE Development in Power System Protection Conference"*, 2002, pp.395-398.

[8] S. M. Brahma and A. A. Girgis, "Fault location on a transmission line using synchronized voltage measurements", "*IEEE Transactions on Power Delivery"*, Vol. 19, No. 4, Oct. 2004, pp. 1619 – 1622.

[9] S. M. Brahma, "Fault location scheme for a multi-terminal transmission line using synchronized voltage measurements", "*IEEE Transactions on Power Delivery"*, Vol. 20, No. 2, April 2005, pp. 1325 – 1331.

[10] S. M. Brahma, " New fault-location method for a single multi-terminal transmission line using synchronized phasor measurements", *IEEE Transactions on Power Delivery*, Vol. 21, No. 3, July 2006, pp. 1148 – 1153.

[11] Eyada A. J. Alanzi , Prof. Mohd Zaid Abdullah , Dr. Nor Ashidi Mat Isa, "Accurate Fault Location of EHV Teed Feeder using RBFNN". "*IJCSNS International Journal of Computer Science and Network Security"*, Vol. 7, No.12, December 2007, pp. 282-286.
[12] Anamika Jain, A.S. Thoke, and R. N. Patel, "Classification of single line to ground faults on double circuit transmission line using ANN", "*International Journal of Computer and Electrical Engineering"*, Vol.1 No. 2, June 2009, pp.197-203.
[13] Math works Inc USA, "*Neural Networks Toolbox*".
[14] Martin T. Hagan and Mohammad B. Menhaj, "Training feedforward networks with the marquardt algorithm", "*IEEE Trans. on Neural Networks*", Vol. 5, No. 6, pp. 989-993, 1994.

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