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Research Article

Artificial Neural Network-Based Fault Distance Locator for Double-Circuit Transmission Lines

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This paper analyses two different approaches of fault distance location in a double circuit transmission lines, using artificial neural networks. The single and modular artificial neural networks were developed for determining the fault distance location under varying types of faults in both the circuits. The proposed method uses the voltages and currents signals available at only the local end of the line. The model of the example power system is developed using Matlab/Simulink software. Effects of variations in power system parameters, for example, fault inception angle, CT saturation, source strength, its X/R ratios, fault resistance, fault type and distance to fault have been investigated extensively on the performance of the neural network based protection scheme (for all ten faults in both the circuits). Additionally, the effects of network changes: namely, double circuit operation and single circuit operation, have also been considered. Thus, the present work considers the entire range of possible operating conditions, which has not been reported earlier. The comparative results of single and modular neural network indicate that the modular approach gives correct fault location with better accuracy. It is adaptive to variation in power system parameters, network changes and works successfully under a variety of operating conditions.

1. Introduction

Protection of double-circuit transmission lines poses additional problems due to zero sequence mutual coupling between faulted and healthy circuits during earth faults [1]. The nature of mutual coupling is highly variable; and it is affected by network changes such as switching in/out of one of the parallel lines, thus causing underreach/overreach of conventional distance relaying [2]. Artificial neural network has emerged as a relaying tool for protection of power system equipments [3]. ANN has pattern recognition, classification, generalization, and fault tolerance capability. ANN has been widely used for developing protective relaying schemes for transmission lines protection. Most of the research on ANN-based protection schemes has been carried out for single-circuit transmission lines [4–16].

An adaptive distance protection of double-circuit line using zero sequence thevenin equivalent impedance and compensation factor for mutual coupling to increase the reach and selectivity of relay has been developed in [2]. Fault classification using ANN for one circuit of parallel double-circuit line has been reported in [17]. A neural network based protection technique for combined 275 kV/400 kV double-circuit transmission lines has been proposed in [18]. The fundamental components of voltages and currents are used as input to neural network for a particular type of fault (single-line to ground) distance location and zone of fault estimation. A novel fault classification technique of double-circuit lines based on a combined unsupervised/supervised neural network has been presented in [19]. It considers only A1G, B2G, A1B1G, and A1C2 faults and other types of faults have not been considered. Cascade correlation algorithm-based ANN is used for fault location and fault resistance determination [20]. Kohonen network is used to improve the accuracy of distance relay for single-line to ground fault on one circuit of double-circuit lines [21]; faults on circuit 2 line have not been considered. The Clarke Concordia transformation, eigenvalue approach, and NN are used to locate the fault of double-circuit line [22]. Adaptive distance relaying scheme for high-resistance faults on two terminal

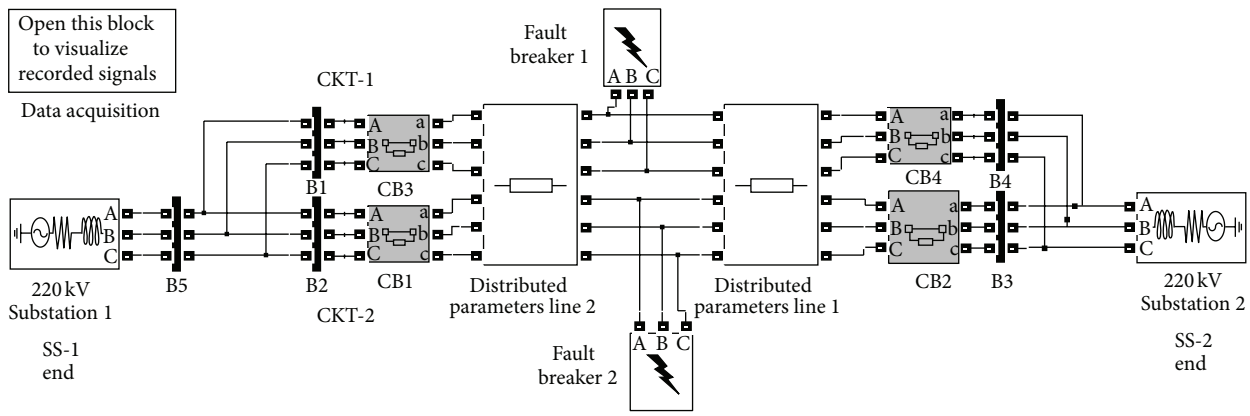

Figure 1: Power system model simulated using Matlab software.

parallel transmission lines using radial basis functions neural network has been reported [23]. It uses changes in active and reactive power flow and resistance as input to RBFNN, and reactance is the output. Only single-line to ground faults was considered in this work.

The work presented in this paper deals with fault distance location using artificial neural network for all the 10 types of faults in a double-circuit transmission lines. Throughout the study a 220 kV double end fed double-circuit transmission line of 100 km length has been chosen as a representative system. The work reports the results of extensive "offline" studies using the Matlab and its associated toolboxes: Simulink, SimPowerSystems and Neural Network Toolbox [24]. The neural networks based protection scheme have been developed for double-circuit transmission line using fundamental components of three-phase voltages and currents in each circuit. The following two ANN architectures were explored for this task:

(i) single neural network for all the 10 type of faults in both the circuits;

(ii) modular neural network for each type of faults (consisting four ANN modules).

All the 10 types of shunt faults (3 phase to ground faults, 3 phase to phase faults, 3 double phase to ground faults, and 1 three-phase fault) on each circuit have been investigated with variation in power system parameters, namely, fault inception angle (Φ_i in °), source strengths at either end (GVA) and its X/R ratio, fault resistance (R_f in Ω), and distance to fault (L_f in km). Additionally, the effects of CT saturation and network changes, for example, double-circuit operation and single-circuit operation with other circuit switched out and grounded at both ends, have also been considered. This encompasses practically the entire range of possible operating conditions and faults which have not been reported in previous works.

2. Power System Network Simulation

A 220 kV double-circuit transmission line of line length 100 km which is fed from sources at each end is simulated using Matlab/Simulink and SimPowerSystems toolbox. The Power system model simulated is shown in Figure 1. The internal impedance of two sources on two sides of the line at SS-1 end and SS-2 end is 45∠82° and 79.5∠85°, respectively. The transmission line is simulated using distributed parameter line model using power line parameter of SimPowerSystems toolbox of Matlab software. The effect of mutual coupling between the two circuits and various types of faults with different system conditions and parameters is considered. Double-circuit transmission line parameters are given in Table 1.

Table 1: Double circuit transmission line parameters.

Parameters	Set value
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	$-2.0444e-009$

3. Single Artificial Neural Network-Based Fault Distance Locator

A single artificial neural network for fault distance location (FDL) of all the ten types of faults in both the circuit under varying power system operating conditions has been developed. The block diagram of the proposed single ANN-based FDL approach is shown in Figure 2.

The implementation procedures for designing the neural network for fault distance location estimation are as follows.

Step 1. Obtain input data and target data from the simulation.

Step 2. Assemble and preprocess the training data for single and modular ANN-based FDL.

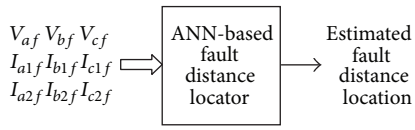

Figure 2: Block diagram of single ANN-based fault distance locator.

Step 3. Create the network architecture and train the network until conditions of network setting parameters are reached.

Step 4. Test and performance analysis.

Step 5. Stored the trained network. Steps 1–5 are offline processes. Next, the network is ready to test with the new input, which is an online process.

Step 6. The new input is preprocessed before presented to the trained single and modular ANN-based FDL.

3.1. Selection of Network Inputs and Outputs. One factor in determining the right size and architecture for the neural 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. The signals recorded at one end of the line only are used. The inputs to conventional distance relays are mainly the voltages and currents. 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 circuit, that is, six currents measured at the relay location. As the basic task of fault location is to determine the distance to the fault, fault distance location, in km (L_f) with regard to the total length of the line, is the only output provided by the fault location network. Thus, the inputs X and the outputs Y for the fault location network are given by:

$$X = \left[V_{af}, V_{bf}, V_{cf}, I_{a1f}, I_{b1f}, I_{c1f}, I_{a2f}, I_{b2f}, I_{c2f}\right], \quad Y = \left[L_f\right]. \tag{1}$$

3.2. Fault Patterns Generation and Preprocessing. To train the network, a suitable number of representative examples of the relevant phenomenon must be selected, so that the network can learn the fundamental characteristics of the problem. The steps involved in fault pattern generation and preprocessing are depicted in Figure 3. Three-phase voltages and three-phase current signals of both the circuits obtained through Matlab simulation are sampled at a sampling frequency of 1 kHz and further processed by simple second-order low-pass Butterworth filter with cut off frequency of 400 Hz. Then one full cycle discrete fourier transform is used to calculate the fundamental component of three-phase voltages and currents of both circuits which are used as input to the ANN. It should be mentioned that the input signals have to be normalized in order to reach the ANN input level (±1). The routine "premnx" of the neural network toolbox of

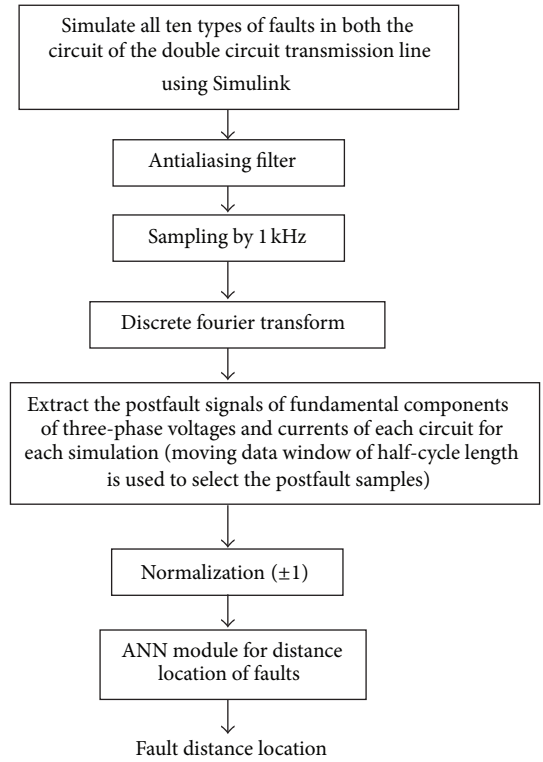

Figure 3: Proposed methodology of ANN-based fault distance location.

Matlab is used to normalize the input signals. For training pattern or input matrix formation, the postfault samples (ten number) of fundamental components of three-phase voltages and currents of each circuit are extracted. For this a moving data window of half-cycle length (which consists of 10 samples) is used to select the postfault data after one cycle from the inception of fault as an input to the artificial neural network. Using Simulink and SimPowerSystem toolbox of Matlab all the ten types of faults at different fault locations between 0 and 100% of line length and fault inception angles 0 and 90° have been simulated as shown in Table 2. The total number of ground faults simulated is $12*10*2*3 = 720$ and phase faults $8*10*2 = 160$; thus total fault cases are 880, and from each fault cases 10 number of postfault samples have been extracted, also 35 no fault samples are taken to form the training data set for neural network. Thus the total number of patterns generated for training is $8800 + 35 = 8835$. Training matrices were built in such a way that the network trained produces an output corresponding to the fault distance location. The proposed methodology of fault distance location using ANN is depicted in Figure 3.

3.3. ANN Architecture. 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 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

Table 2: Training patterns generation for single and modular ANN-based FDL.

Parameter	Set value
Fault type	LG: A1N, A2N, B1N, B2N, C1N, and C2N LL: A1B1, A2B2, B1C1, B2C2, A1C1, and A2C2 LLG: A1B1N, A2B2N, B1C1N, B2C2N, A1C1N, and A2C2N LLL: A1B1C1, A2B2C2
Fault location (L_f in KM)	1, 10, 20, 30, . . ., 80, and 90 KM
Fault inception angle (Φ_i)	0° and 90°
Fault resistance (R_f)	0, 50 and 100 Ω
Prefault power flow angle (δ_s)	45°

Table 3: Comparison of ANN models for FDL.

S. number	Number of hidden neurons	Number of epochs	Mean square error
1	10	300	0.0116445
2	15	300	0.0067783
3	20	300	0.0021979
4	25	300	0.000853473
5	30	300	0.000645901
6	35	300	0.000557819
7	40	300	0.000466127

is no parametric/theoretic guidance available, the design has to be based on a heuristic approach. The ANN architecture, including the number of inputs to the network and the number of neurons in hidden layers, is determined empirically by experimenting with various network configurations. Through a series of trials and modifications of the ANN architecture, the best performance is achieved by using a three-layer neural network with 9 inputs, 1 output, and the optimal number of neurons in the hidden layer was found to be 40 (as per comparison of different ANN models shown in Table 3). The architecture of single ANN-based fault locator (9-40-1) is shown in Figure 4 [25–28].

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. Purely linear transfer function (purelin) has been used in the output layer as the output is fault distance location which varies between 0 and 100 KM linearly.

3.4. Training Process. Various learning techniques were applied to the different network architectures, and it was concluded that the most suitable training method for the architecture selected was based on the Levenberg-Marquardt (LM) technique, as it gives fastest convergence [29]. The

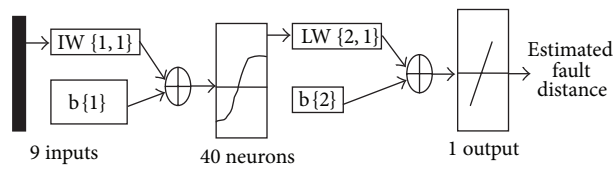

Figure 4: Architecture of single ANN-based fault distance locator.

single ANN-based FDL was trained by LM training algorithm. This learning strategy converges quickly, and the mean squared error (mse) decreases in 300 epochs to $4.66127e-04$ in around 15 minutes computation time on a PC (P4, 2.66 GHz, and 2 GB RAM). The single ANN-based FDL requires large training sets (all types of faults in both circuit with varying fault parameters) and long training time. Also the network complexity is higher, and it has slower learning capability. However, once the network is trained sufficiently with large training data set, the network gives the correct output when subjected to fault situations. The test results of single and modular ANN-based FDL are discussed in Section 5.

4. Modular Artificial Neural Network-Based Fault Distance Locator

The single ANN-based FDL has the disadvantages of complexity, large training sets, long training time, and slow learning capability. Thus, it was decided to develop a modular neural network for each type of faults. In this approach any task is divided into number of possible subtasks where each one is accomplished by an individual neural network. Finally, all network outputs are integrated to achieve the overall task. Obviously the approach has the advantages of simplicity, higher accuracy, less training sets and training time, easier interpretation, model complexity reduction, and better learning capability.

In modular approach, on the occurrence of a fault, the fault detection/classification unit [25–28, 30] activates the modular ANN-based fault distance locator unit. Four different ANN-based fault detector and classifier modules have been developed according to type of fault, that is, LG, LL, LLG, and LLL as shown in Figure 5. The output of ANN-based fault detector and classifier modules are

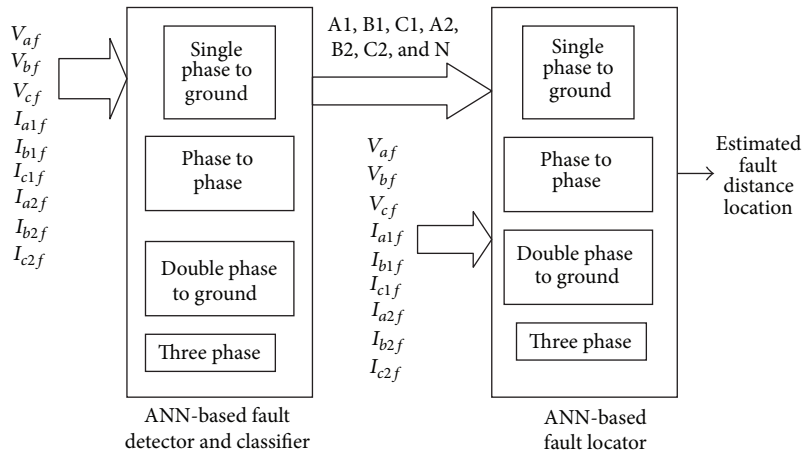

Figure 5: Block diagram of modular ANN-based fault distance locator.

Table 4: Architecture of modular ANN-based fault distance locator.

S. No.	Modular ANN-based fault distance locators	Architecture	Mean square error (MSE)
1	Phase to ground	9-30-7	$5.02509e-04$
2	Phase to phase	9-30-7	$2.0906e-04$
3	Double phase to ground	9-20-7	$2.7078e-04$
4	Three phase	9-5-7	$8.52572e-005$

total seven: three-phases of each circuit A1, B1, C1, A2, B2, C2, and N neutral to determine whether fault involves ground or not. Based on the fault type which occurs on the system, output should be 0 or 1 in corresponding phase(s) and neutral. Fault detection/classification unit detects and identifies the type of fault and thus activates the particular type of fault locator to estimate the fault distance location. The inputs and output of modular ANN-based FDL are the same as selected for single ANN-based FDL approach, that is, total (9) inputs and one (1) output. The procedure of development of the architecture of modular ANN-based FDL is same as that is single ANN-based FDL. The block diagram of the proposed modular ANN-based FDL approach is shown in Figure 5. The fault location unit comprises of four feed forward neural networks, one network each for the four categories of fault (LG, LL, LLG, and LLL). The final architectures of modular ANN-based FDLs are shown in Table 4.

5. Comparison of Test Results of Single and Modular ANN-Based Fault Distance Locator

After training, single and modular ANN-based FDLs were extensively tested using independent data sets consisting of fault samples never used previously in training. The network was tested by presenting fault patterns with varying fault type, distance locations ($L_f = 0$–95 km), fault inception angles ($\Phi_i = 0$–360°), and fault resistance ($R_f = 0$–$100\,\Omega$). Additionally, the effect of change in source strength at end, CT saturation, prefault power flow angle, fault resistance, and single-circuit operation is also studied. The test results of single and modular ANN-based FDLs under different fault conditions are depicted in Table 5. At various locations different types of faults were tested to find out the maximum deviation of the estimated distance L_e measured from the relay location and the actual fault location L_f. Then the resulting estimated error "e" is expressed as a percentage of total line length L as

$$e = \frac{L_f - L_e}{L_f} \times 100\%. \tag{2}$$

It can be seen from the test results in Table 5, that the % error in locating the fault using single ANN-based FDL is within −1.973% to 7.162%, and that of modular ANN-based FDL lies between −1.362% and 1.201%. Thus, modular ANN-based FDL determines the fault distance location more accurately than the single ANN-based FDL. Some of the simulation results under different fault situations with varying power system parameters are discussed below. The extreme fault cases near to the source end (1 km) and at far end of the line (90 km) were also investigated.

5.1. Phase to Phase Fault with Varying Source Strength. During training, the strengths of both the sending and receiving end sources (GVA and X_s/R_s ratio) were taken as 1.25 GVA its X_s/R_s ratio is 10, and it is tested by varying the strengths of either end. To check the performance of the proposed techniques, the test conditions simulated is "A2C2" fault at 18 km from "SS-1" end. Fault has occurred at 65 ms ($\Phi_i = 90^\circ$), $\delta_s = 45^\circ$; source at SS-1 end has strength of 1.25 GVA, and its X_s/R_s ratio is 10; source at SS-2 end has strength of

Table 5: Test results of single and modular ANN-based fault distance locator.

Fault type	Fault inception angle Φ_i (°)	Fault resistance R_f (Ω)	Fault location L_f (km)	Output of single ANN-based FDL L_e (km)	Output of modular ANN-based FDL L_e (km)	% Error of single ANN-based FDL $e = ((L_f - L_e)/L_f) \times 100\%$	% Error of modular ANN-based FDL $e = ((L_f - L_e)/L_f) \times 100\%$
A1N	45	80	67	64.470	66.95	2.53	0.05
A2N	90	90	77	76.447	57.111	0.553	−0.111
B1N	135	0	5	4.9724	4.8895	0.0276	0.1105
B2N	270	80	89	88.624	88.681	0.376	0.319
C1N	360	95	95	92.405	94.604	2.595	0.396
C2N	180	70	38	35.449	38.385	2.551	−0.385
A1B1	270	—	83	83.020	83.25	−0.02	−0.25
A2B2	0	—	15	15.066	15.009	−0.066	−0.009
B1C1	0	—	76	75.049	75.894	0.951	0.106
B2C2	135	—	90	89.490	89.977	0.51	0.023
C1A1	90	—	22	22.144	22.134	−0.144	−0.134
C2A2	225	—	59	58.762	58.984	0.238	0.016
A1B1N	135	30	85	82.955	83.799	2.045	1.201
A2B2N	45	60	57	56.459	56.047	0.541	0.953
B1C1N	225	100	88	88.246	88.1006	−0.246	−0.1006
B2C2N	270	80	89	88.632	90.133	0.368	−1.133
C1A1N	225	30	58	50.838	57.047	7.162	0.953
C2A2N	90	40	24	20.105	25.362	3.895	−1.362
A1B1C1	225	—	33	33.757	32.952	−0.757	0.048
A2B2C2	360	—	85	86.973	85.136	−1.973	−0.136

0.25 GVA, and its X_s/R_s ratio is 5. During any fault situation in any one circuit of the double-circuit line which is fed from sources at both the ends as shown in Figure 6, remote end source also feed current to the fault point. This remote end infeed is not measurable at the relay location which causes the conventional relays to mal-operate.

Test results of single and modular ANN-based FDL for a phase to phase fault in circuit 2 with variation in source strength are shown in Figures 7(a) and 7(b), respectively. The neural network is trained to show the output as 100 km for no fault situations or fault outside the zone of protection. For faults within its zone of protection, it will show the estimated fault distance location. The output of single and modular ANN-based FDLs during prefault or steady-state conditions is around 110 km, as the networks are trained with a target location 110 km which is outside the line segment as shown in Figures 7(a) and 7(b), respectively. After the inception of the fault the algorithm takes one cycle to get the correct estimate of the fault distance location. The output of single and modular ANN-based FDLs at 98 ms is 18.5849 km and 18.1617 km as against 18 km, respectively. This shows that the modular ANN-based FDL has more accuracy in fault distance estimation as compared to single ANN-based FDL; however, the operating time of both the algorithms is more than one cycle time.

The reason behind the statement "operating time is after one cycle" is that one full cycle DFT is used to estimate the fundamental components of three-phase currents and

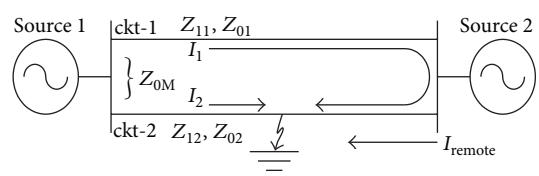

Figure 6: Single-line diagram of a three-phase double-circuit line connected with source at each end under fault condition.

voltages which is further given to ANN for fault distance location estimation. The estimation of fundamental components by DFT is being done continuously, thus immediately after the fault occurrence there is increase in the estimate of fundamental components of corresponding phase currents involved in the fault loop and decrease in estimate of fundamental components of corresponding phase voltages. ANN-based FDLs detects these changes (decrease) in fundamental components of voltages and (increase) currents, and its output decreases from the 110 km to the desired value after one-cycle time when the correct estimates of voltage and current are obtained (after one cycle from the inception of fault because of 1-cycle DFT).

5.2. Double Phase to Ground Fault with High Fault Resistance. When fault occurs with high fault resistance, the conventional

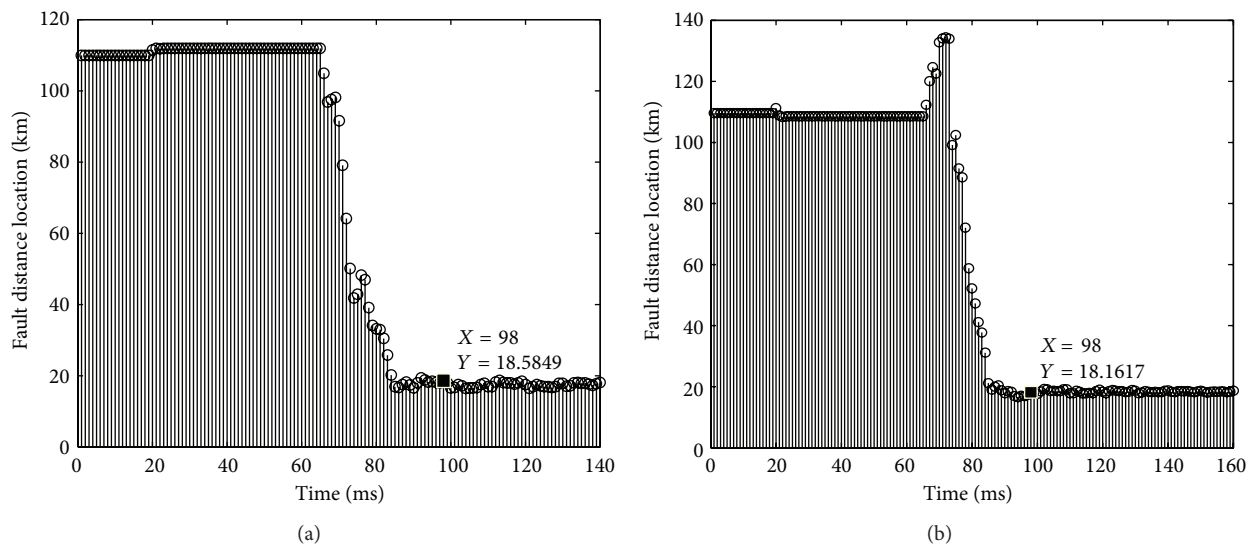

Figure 7: Test results of single and modular ANN-based FDL for "A2C2" fault in ckt-2 at $\Phi_i = 90^\circ$ (inception time 65 ms) at 18 km, $\delta_s = 45^\circ$, SS-1 end source strength =1.25 GVA, $X_s/R_s = 10$, and SS-2 end source strength = 0.25 GVA, $X_s/R_s = 5$, respectively.

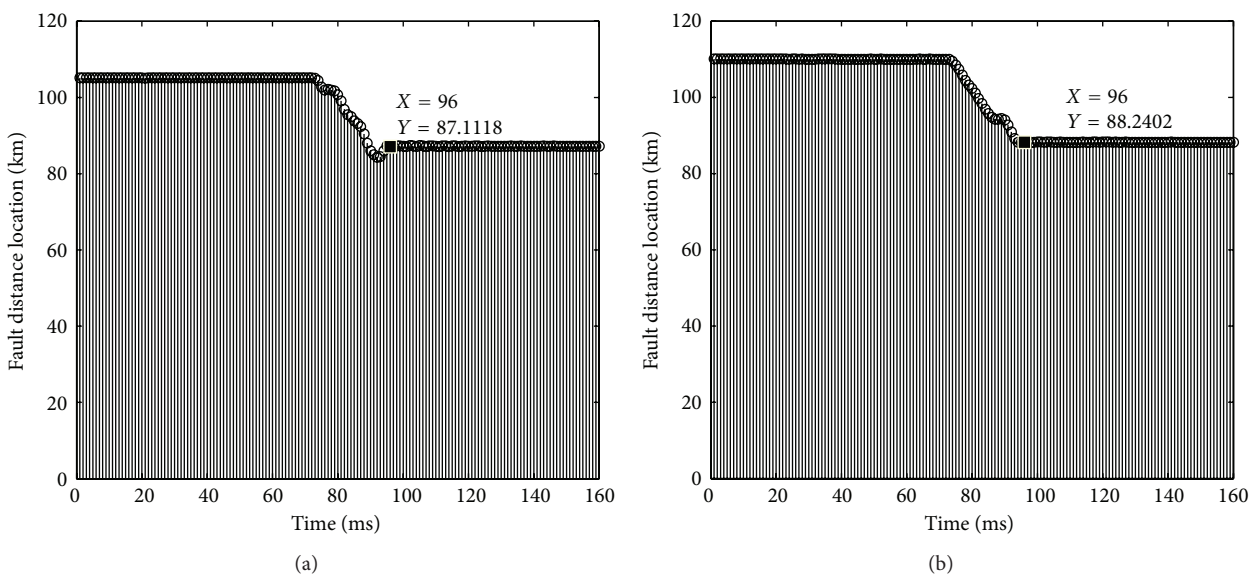

Figure 8: Test results of single and modular ANN-based FDL during "B1C1G" fault at 88 km from SS-1 end at 72.5 ms ($\Phi_i = 225^\circ$) with $R_f = 100\,\Omega$, $\delta_s = 45^\circ$, respectively.

distance relays under reach due to conversion of the fault resistance into effective fault impedance. To study the effect of high fault resistance a double phase to ground fault has been simulated with high fault resistance. Test conditions were "B1C1G" fault at 88 km from "SS-1" end with $R_f = 100\,\Omega$ and occurred at 72.5 ms with $\Phi_i = 225^\circ$. Test results of single and modular ANN-based FDLs under this condition are shown in Figures 8(a) and 8(b). After one cycle from the inception of fault (72.5 ms), that is, 92.5 ms, the fundamental components of three-phase voltages and currents in both circuit are estimated correctly by DFT, thereafter the ANN-based algorithm gives correct result. As shown in Figures 8(a) and 8(b) at 96 ms, the outputs of single and modular ANN-based FDL are 87.11 km and 88.2402 km, respectively, as against the set value of 88 km.

5.3. Three-Phase Close in Fault. When fault occurs very near to the source end where the relays are installed, it is called as a close in fault. A three-phase close in fault is simulated in ckt-2 of the selected power system model at 1 km from SS-1 end. Test conditions were "A2B2C2" fault at 1 km from "SS-1" end with $R_f = 0\,\Omega$ and occurred at 77.5 ms with $\Phi_i = 225^\circ$. Test results of single and modular ANN-based FDLs under this condition are shown in Figures 9(a) and 9(b), respectively. From the Figure 9(a), it can be seen that

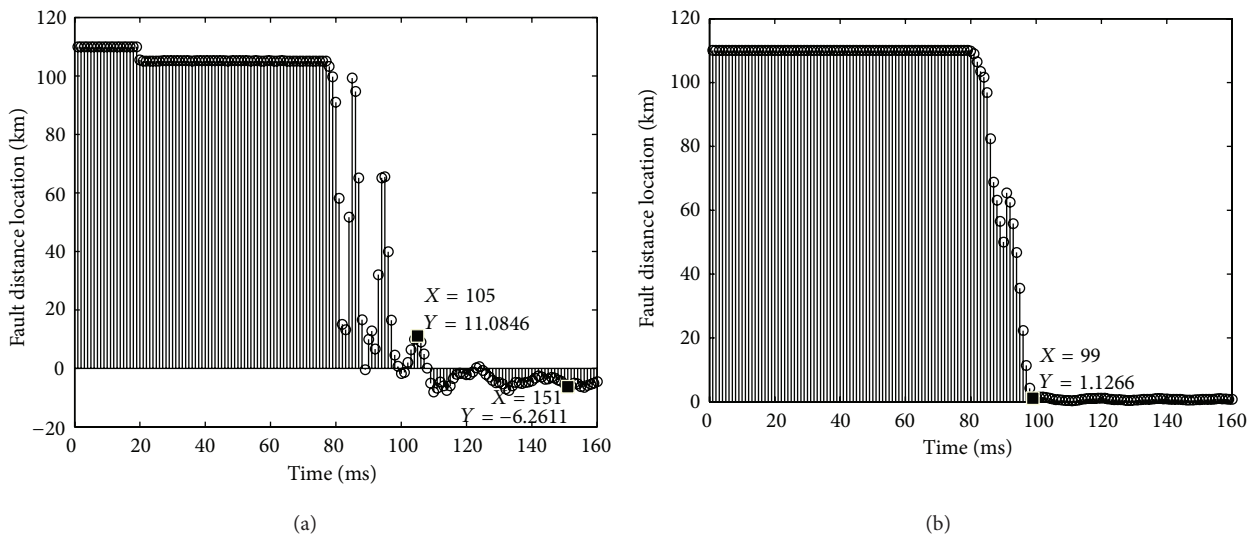

Figure 9: Test result of single and modular ANN-based FDL during "A2B2C2" fault at 1 km from source "SS-1" at $\Phi_i = 315^\circ$ (fault inception time 77.5 ms) and $\delta_s = 45^\circ$, respectively.

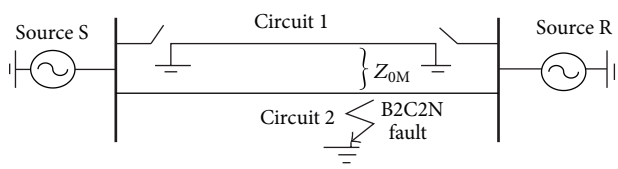

Figure 10: Double-circuit line with ckt-1 out of service, opened and grounded, and fault in ckt-2.

the single ANN-based FDL output fluctuates between 11.0846 km and −6.2611 km and finally settles at the later value as against the set value of 1 km. The output is negative for most of time; this is because the transfer function in the output layer is pure linear. Thus it is concluded that single ANN-based FDL is not able to locate the close in fault.

On the other hand the output of the modular ANN-based FDL after one cycle from the inception of fault (77.5 ms), that is, at 99 ms, is 1.1266 km instead of 1 km actual fault location as shown in Figure 9(b). Further the output is almost constant around 1 km. Thus it is clear that modular ANN-based FDL can precisely locate the close in three-phase fault also.

5.4. Single-Circuit Operation. The conventional distance relays overreach when both circuits are in service and underreach if one of the circuits is out of service and earthed at either ends [19]. The performance of single and modular ANN-based FDLs during fault in ckt-2 when ckt-1 is out of service and grounded is investigated as shown in Figure 10. For example, ckt-1 opened and grounded and double phase to ground fault in ckt-2, that is, "B2C2N" fault at 60 km from SS-1 end at 40 ms ($\Phi_i = 0^\circ$) with $R_f = 50\,\Omega$, $\delta_s = 45^\circ$ are examined.

Test results of single and modular ANN-based FDL are shown in Figures 11(a) and 11(b). The output of the single and modular ANN-based fault locators is 60.0222 km and 60.012 km at 63 ms, that is, after one cycle from the inception of fault as shown in Figures 11(a) and 11(b), respectively. This shows that the networks respond correctly and accurately when the double-circuit line is operated as a single-circuit line and there is fault in the healthy circuit. It can be concluded that ANN-based FDLs are adaptive to network changes, namely, double-circuit and single-circuit operation modes.

5.5. Single Phase to Ground Fault with CT Saturation. The test results of single and modular ANN-based FDL with CT saturation taken into account are shown in Figures 12(a) and 12(b), respectively. The test condition is single phase to ground fault applied on C1 phase of ckt-1, that is, "C1N fault at 60 ms ($\Phi_i = 0^\circ$) at 90 km from "SS-1" end with $R_f = 0\,\Omega$ and $\delta_s = 45^\circ$. It is observed from Figure 12(a) that the estimated fault distance by single ANN-based FDL during the same fault conditions with CT saturation taken into account has some variations. During prefault condition, the output is around 110 km, that is, out of the protected zone. At 86 ms output shows 90.6503 km as against the set value of 90 km. However, the estimated fault distance by modular ANN-based FDL at 86 ms is 89.8859 km as against 90 km actual fault distance as shown in Figure 12(b). This shows that the modular ANN-based FDL has more accuracy in fault distance estimation as compared to single ANN-based FDL.

6. Comparison with the Existing Schemes

The proposed modular ANN-based FDLs scheme is compared with the some of the reported works employing ANN. The proposed modular ANN-based fault locator scheme is developed for all the ten types of faults in both the circuits with wider range of fault resistance, fault inception angle, and source strengths variations which had been used for training pattern generation shown in Table 2. Once the network is trained its structural parameters are fixed

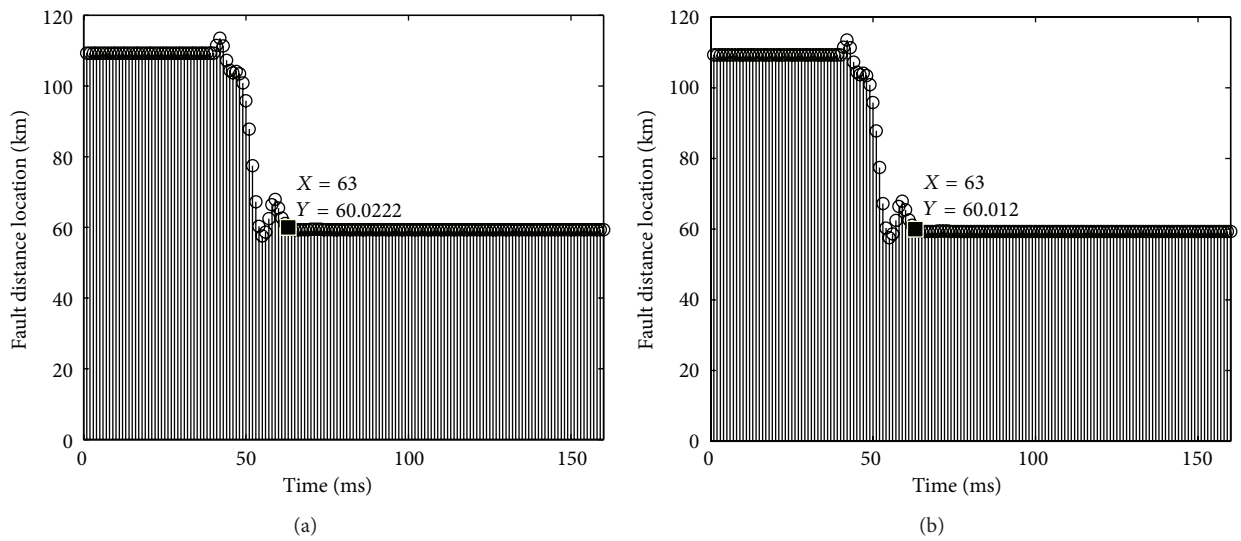

Figure 11: Test result of single and modular ANN-based FDL during "B2C2N" fault at 60 km from SS-1 end at 40 ms ($\Phi_i = 0^\circ$) with $R_f = 50\,\Omega$, $\delta_s = 45^\circ$, respectively.

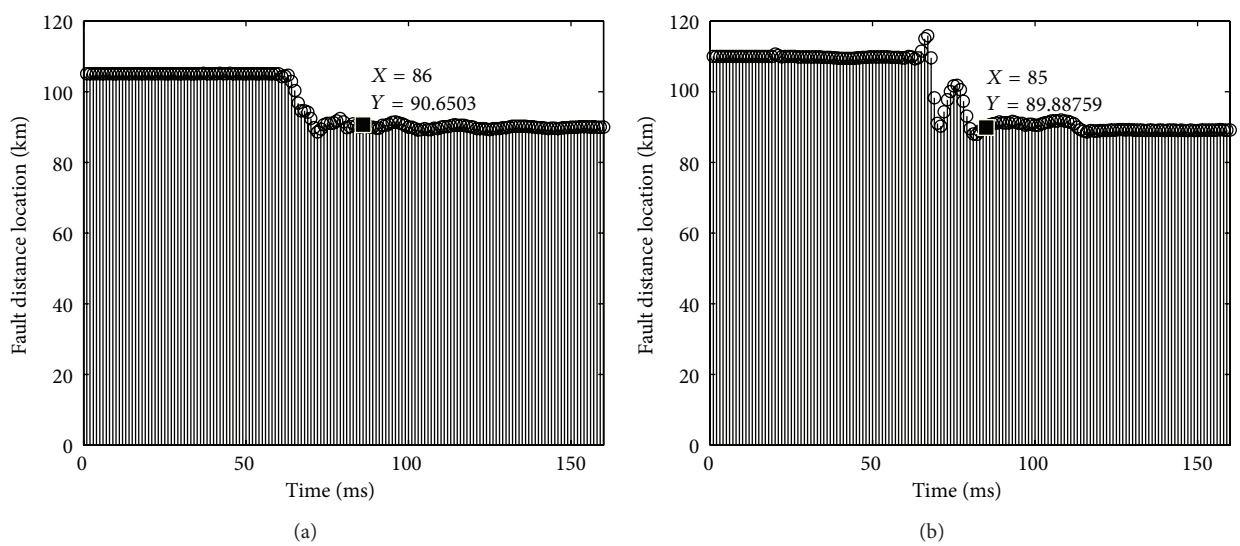

Figure 12: Test results of single and modular ANN-based FDL *with CT saturation* taken into account during "C1N" fault at 60 ms ($\Phi_i = 0^\circ$) at 90 km from "SS-1" end with $R_f = 0\,\Omega$ and $\delta_s = 45^\circ$, respectively.

(i.e., number. of layers, neurons, weight, bias, etc.). Further it is tested for different fault situation that has been not used during training of the network. The effects of remote source infeed, zero sequence mutual coupling, CT saturation, and network changes, for example, single-circuit operation, have also been considered without training the network again. The salient features of some of the existing ANN-based fault location schemes and the proposed scheme is presented in Table 6. Accuracy of the algorithm are lies between −1.362% and 1.201% as shown in Table 5 is which is quite good when compared to existing schemes. Response time of the proposed scheme for detection of the fault and distance location estimation is 1 cycle from the inception of fault which is comparable to the conventional distance relay.

7. Conclusions

Single and modular neural network modules were developed for determining the fault distance location in double-circuit transmission lines. The test results of single and modular ANN-based FDLs have been shown under variety of the fault situations, namely, LG faults (A1N, A2N, B1N, B2N, C1N, and C2N), LL faults (A1B1, A2B2, B1C1, B2C2, C1A1, and C2A2), LLG faults (A1B1N, A2B2N, B1C1N, B2C2N, C1A1N, and C2A1N), and LLL faults (A1B1C1 and A2B2C2). Also, variations in the power system parameters, namely, fault locations (0–95%), fault resistances (0–100 Ω), fault inception angles (0–360°), source strengths, CT saturation, and network changes, for example, single-circuit operation, have

Table 6: Comparison of neural network-based fault location schemes.

Schemes suggested by authors	Fault locator inputs	Line configuration	Fault resistance R_f range (Ω)	Fault inception angle Φ_i (°)	Other factors considered	Response time and accuracy
Mahanty and Gupta [13]	Samples of 3-phase V and I	Single-circuit line for LG and LL faults only	0–200	0–90°	Other types of faults and wide variation in inception angle not considered.	Response time not indicated and error is 6%.
Mazon et al. [9]	Samples of 50 Hz components of 3-phase voltages and currents of each circuits	Double-circuit line for LG faults only	0–20	—	Other types of faults and variation in inception angle not considered.	Response time not indicated and error is 0.19%.
Bhalja and Maheshwari [23]	Δp, δq, and resistance	Double-circuit line for LG faults only	0–200	—	Mutual coupling, remote source infeed.	Not indicated.
Singular distance locator (by Jain et al.) [25]	Samples of 50 Hz components of 3-phase voltages and currents of each circuits	Double-circuit line for all 10 types of faults in both the circuits (total 20 types of faults)	0–100	0–360°	Mutual coupling, remote source infeed, and all 10 types of faults in each circuit.	1-cycle time from inception of faults and % error is from −7% to +1.97%.
Proposed scheme (modular distance locator)	Samples of 50 Hz components of 3-phase voltages and currents of each circuits	Double-circuit line for all 10 types of faults in both the circuits (total 20 types of faults)	0–100	0–360°	Mutual coupling, remote source infeed, all 10 types of faults in each circuit, source strength variation, CT saturation, and single-circuit operation.	1-cycle time from inception of faults and % error is from −1.362% to +1.201%.

been considered. The comparison of the test results of single and modular approach shows that the modular approach is more accurate. The modular ANN-based FDLs test results are very encouraging and confirm the suitability of the technique for protection of double-circuit transmission line. The ANN-based fault locators calculates the fault distance up to 0–90% of the line length with high accuracy and enhances the performance of distance relaying scheme by increasing its reach setting. The proposed technique can be applied as an alternative protection scheme or a supplement to existing schemes.

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