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Abstract

This paper presents an artificial neural network- (ANN) based approach to improve the performance of the distance relaying algorithm. The proposed distance relay uses magnitudes of voltages and currents as input signals to find fault locations. In this approach, an ANN has been included in the protection algorithm as an extension of the existing methods, which improves the reliability of the protection operation. The design procedure of the proposed relay is presented in detail. Simulation studies are performed and the influence of changing system parameters, such as fault resistance and source impedance, is studied. Performance studies show that the proposed algorithm is accurate and reliable.

Key Words: *Artificial neural networks, adaptive distance protection, transmission line, pattern recognition.*

1. Introduction

Among the components of an electric power system, the transmission line is the most susceptible element to experience faults, especially if its physical dimension is considerable. Different kinds of faults can occur between a conductor and ground (single-line-to-ground faults), 2 conductors and ground (phase-to-phase-to-ground faults), 2 conductors (phase-to-phase faults), or 3-phase faults.

Distance relaying techniques have attracted considerable attention for the protection of transmission lines. The principle of these techniques is the measurement of impedance at a fundamental frequency between the relay location and the fault point; thus, determining if a fault is internal or external to a protection zone. Voltage and current data are used for this purpose and they generally contain the fundamental frequency signal, harmonics, and DC offset.

Initial efforts in fault location estimation rely on the determination of transmission line impedance using specific line models that consider certain real-world effects, such as harmonics, arcing faults, current-transformer-saturation, etc. However, none of those models considers all possible effects and the erroneous trip decisions resulting from that would undermine the dynamic stability of the power system [1, 2].

Protective relaying is a very good candidate for the application of pattern recognition. The majority of power system protection techniques involve defining the system state by identifying the pattern of the associated voltage and current waveforms measured at the relay location. This means that the development of adaptive protection can be essentially treated as a problem of pattern recognition and classification. Artificial neural networks (ANNs) are powerful in pattern recognition and classification. They possess excellent features, such as generalization capability, noise immunity, robustness, and fault tolerance. Consequently, the decision made by an ANN-based relay will not be seriously affected by variations in system parameters. ANN-based techniques have been used in power system protection and encouraging results have been obtained [3-8].

Some of the published results of the application of ANNs in protective relaying are related to the improvements in distance relaying. A survey on the distance relaying-related applications is given in [6]. Ref. [9] demonstrates the use of neural networks as a pattern classifier for the distance relaying algorithm and shows that the proposed scheme improves protection system selectivity. Ref. [10] uses a multilayer feedforward network to reduce the influence of DC offset on fault distance computation. Saturation of current transformers (CT) during a heavy fault could cause incorrect distance measurement by the distance relay. Ref. [11] introduces an ANN-based approach that is immune to CT saturation effects. Application of the distance relaying algorithm on series-compensated transmission lines could result in major problems causing erroneous operation of distance relays. An ANN-based algorithm has been proposed in [12] for locating faults on series-compensated transmission lines. Some ANN-based approaches are based on analyzing high frequency signals generated by a fault. A wide frequency range from zero to 100 kHz has been used in [13]. However, measurement of high frequency signals using conventional current and voltage transformers might cause some error.

In this paper, an ANN-based approach, which adds one artificial neural network to the existing digital distance algorithm, is used to design an accurate and reliable distance relay. Application of the proposed algorithm reduces the effects of system variables, such as fault resistance, source impedance, and decaying DC offset, on the decision made by the distance relay. It is shown that the proposed relay is able to accurately distinguish between faults inside and outside of its protection zone, under different system conditions. The proposed approach has been tested to evaluate its performance in terms of accuracy, robustness, and reliability.

2. Basic Structure of the Proposed Approach

Figure 1 shows the block diagram of the proposed approach. First, a distance relay determines fault locations with the DFT algorithm. This distance relay includes 3 units for phase to ground faults and 3 units for phase to phase faults. If the fault location is distinguished approximately within 15% of the reach zone, the ANN makes the final decision; otherwise, the ANN is bypassed and the distance relay with the DFT algorithm is used to make the trip desicion.

Pre-processed voltages and currents are used as inputs to the ANN, which determines the fault location. Finally, a logic unit issues the trip order based on the output of the DFT algorithm and the output of the ANN. The following equations show the trip decision-making process used by the logic unit:

$$\begin{cases} R_f < 0.85.Rs + m.X_f \ , \ X_f < 0.85.X_s \ \Rightarrow \ trip \\ 0.85.R_s + m.X_f < R_f < 1.15.R_s + m.X_f \ , 0.85.X_s < X_f < 1.15.X_s \ \Rightarrow \begin{cases} outANN > 0.9 \Rightarrow \ trip \\ outANN < 0.1 \Rightarrow \ Notrip \end{cases} \\ R_f > 1.15.R_s + m.X_f \ , \ X_f > 1.15.X \Rightarrow \ Notrip \end{cases}$$

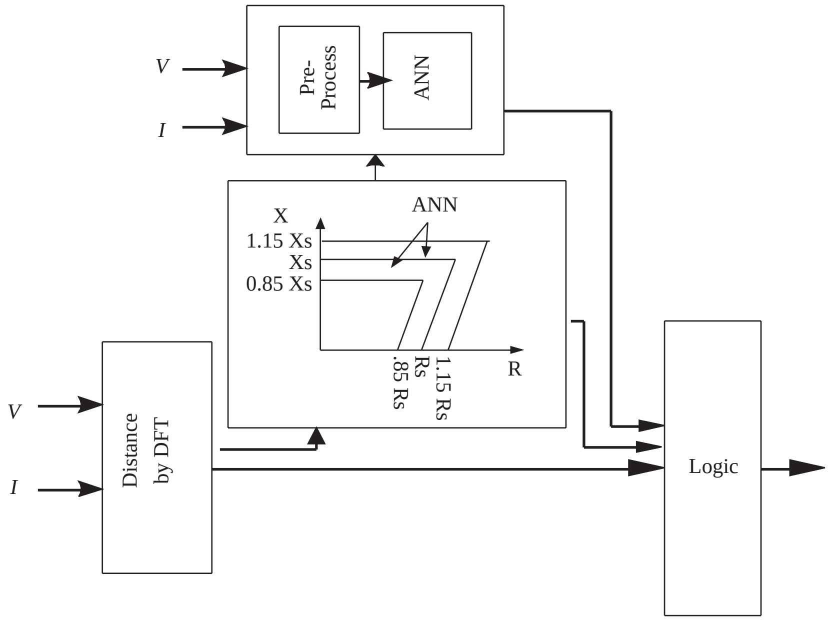

Figure 1. The proposed relay structure.

In these equations, Rf and Xf are resistance and reactance of the fault measured by the DFT algorithm. Rs and Xs are reach of the protection zone, as shown in Figure 1. The DFT algorithm cannot distinguish the fault location within 15% of the reach zone because of malfunction of conventional algorithms near the zone's boundary. Therefore, the ANN will be activated and make the trip decision in this region.

3. Simulation of the Power System

In order to test the applicability of the proposed approach, a simulation using EMTDC [14] is done for a transmission line under different faulted conditions assuming perfect line transposition. The 100 km, 230 kV transmission line used to train and test the proposed ANN is shown in Figure 2, and parameters of the transmission line are presented in Table 1. The combinations of faults generated for training the ANN in this power system are shown in Table 2.

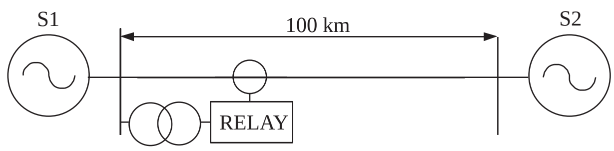

Figure 2. Simulated power system model.

Table 1. Simulated power system parameters.

Positive and negative sequence line impedances (Ω/km)	0.072 + j 0.416
Zero sequence line impedance (Ω/km)	0.346 + j1.066
Sources' impedances (Ω)	41.7
Sources X/R ratios	10
Sources Zo/Z1 ratios	0.5

Table 2. Training patterns data generation.

Fault Type	Single phase to ground, phase to phase to ground, phase to phase, and 3-Phase
Fault Location (km)	25, 50, 70, 75, 79, 80, 81, 85, 90, 95
Fault Resistance (Ω)	Different values between (0 and10)
Inception Angle (deg)	Different values between (0 and 360)
Load Angle (deg)	Different values between (+10 and -10)

It is assumed that the relay is to protect 80% of the line, i.e., 80 km. Fault data are generated at different distances for various fault types, fault resistances (0-10), and fault inception angles. By studying the changes in voltages and currents of different phases with the changes in load angles, it is determined that load angles must be considered in training the ANN.

4. Network Input Selection

Neural networks have the ability to classify different input patterns into desired output classes. The application of a pattern classification technique requires a selection of features that contain the information needed to discriminate between classes, and that permit efficient computation by limiting the amount of training data and the size of network.

Most of the necessary information for determining disturbances and transients in power systems is usually contained in the voltage and current waveforms. Figures 3 and 4 show the change of voltages and currents with the change of fault location. Figure 3 shows that the magnitudes of voltages and currents are functions of fault locations for a single-phase fault. Figure 4 shows that magnitudes of voltages and currents change with the change of power angle in a power system for 3-phase faults in two different locations, 78 km and 82 km.

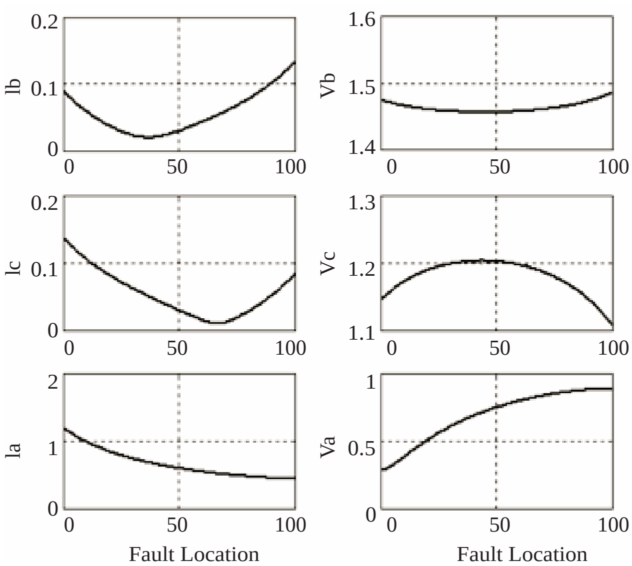

Figure 3. Magnitudes of voltages and currents as functions of fault locations for a single-phase fault.

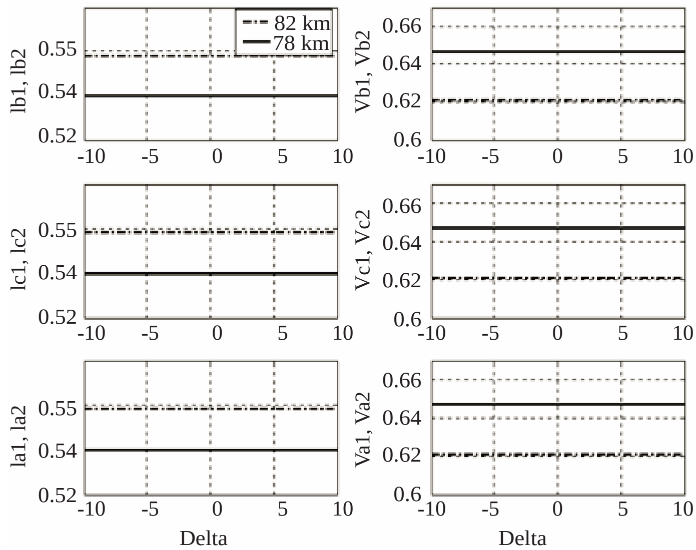

Figure 4. Magnitudes of voltages and currents as functions of power angles for a 3-phase fault in 2 different locations; 78 km and 82 km.

Simulation studies show similar results for other faults and other conditions (power angle, fault resistance, etc.). This means that the magnitudes of voltages and currents are not the same for 2 different fault conditions. Thus, the magnitudes of voltages and currents can be suitable inputs for ANN-based distance relay, and this has been verified by our extensive studies, which show that a neural network using magnitudes of 3-phase currents and voltages is able to distinguish fault location.

5. Pre-Processing

In general, pre-processing is a useful method to reduce the dimensions of the input data set. In the ANN-based distance relay, pre-processing can reduce the size of the neural network significantly, which in turn, improves the performance and speed of the training process [15]. In addition, when a fault occurs on a transmission line, voltage and current signals develop a decaying DC offset component whose magnitudes depend on many factors that are random in nature. Furthermore, voltage and current signals are often noisy when faults occur; thus, the input data should be pre-processed before they are fed to the network.

The process of generating input patterns from the recorded voltages and currents is depicted in Figure 5. First, the 3-phase voltages and currents at the relay location are obtained from the EMTDC. These samples are processed by 2nd order low pass anti-aliasing filters and are resampled at 1 kHz. The anti-aliasing filters have a cut-off frequency of 100 Hz. A 2-sample FIR digital flitter then removes the DC component. Elimination of the DC component enhances the training capabilities of the ANN-based distance relay.

Voltage and current samples are scaled to have a maximum value of +1 and a minimum value of –1. This is achieved by using a scaling factor equal to the peak value of the normal rated voltage for the voltage samples, and 6 times of the peak value of normal rated current for the current samples. Patterns are then generated using the processed voltage and current samples.

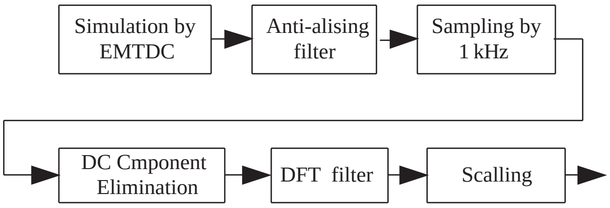

Figure 5. Pre-processing of input patterns.

6. Network Structure and Training

The ANN architecture employed here is a multi-layer perceptron network based on data obtained from simulated waveforms. Magnitudes of the voltage and current phasors are inputs to the ANN.

In order to obtain the magnitudes and phase angles of such waves, the full cycle Discrete Fourier Transform (DFT) filter is utilized. For this approach, only the magnitudes of fundamental frequency voltage and current waveforms (not the phase angles) are utilized as the inputs to the networks, i.e., magnitudes of 3-phase voltages ($|va|$, $|vb|$, $|vc|$) and currents ($|Ia|$, $|Ib|$, $|Ic|$).

The approach should differentiate faults within 80% of the line length from faults outside that zone, giving 1 and 0, respectively. For faults inside the protection zone, a trip signal should be sent to the circuit breaker.

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 trial and error, and modifications of the ANN architecture, the best performance is achieved by using a 3-layer perceptron with 6 inputs and 1 output. The number of neurons for the 2 hidden layers is 12 and 6, respectively. The transfer function of the network neurons is the hyperbolic tangent and the ANN performs best using the Levenberg-Marquardt training algorithm [16, 17].

7. Test Results

A. Initial Performance Studies

A validation data set consisting of about 100 different fault types are generated using the power system model shown in Figure 1. Fault patterns in the validation set are different from those for training the network. Fault type, fault location, fault inception time, source impedance, and pre-fault power flow direction in the validation data set are changed to investigate the effects of these factors on the performance of the proposed approach. Extreme cases, such as faults with fault resistance occurring close to the boundary of the protection zone, are also included in the validation data set. For the studies performed in this section, the first protection zone is set to 80 km.

The performance of the proposed distance relay is further evaluated by comparing its results with the results obtained from a conventional digital distance relay. The operation time for the proposed distance relay and the conventional distance relay with the DFT algorithm is presented in Table 3, for several faults under different power system conditions. The first row of Table 3 shows an example for a single-phase to ground, AG fault at 20 km from the relay location. For this fault, the relative angle of the sending–end source with respect to the angle of the receiving-end source is 30 degrees. The fault inception angle with respect to phase A voltage is 10 degrees.

Relay operation time for 3 different fault resistances is shown in the last 3 columns of Table 3. For the faults, which involve ground, the relay operation time for 0, 5, and 10 Ω fault resistance is investigated. For the faults, which do not involve ground, only relay performance, without fault resistance is investigated since fault resistance is not a critical factor.

As shown in Table 3, the proposed relay performs accuratly and reliably. The proposed distance relay operates for the faults inside the first protection zone. It also operates for the faults including 10 Ω fault resistance, to which conventional relays are not able to responsd. For the faults outside of the first protection zone, where the conventional relays malfunction, the proposed relay does not operate as expected. Based on these studies, as well as many other different simulation studies that have been performed, it is found that the ANN-based relay is able to perform more accurately and reliably when compared with conventional distance relays.

Table 3. Distance relay test results.

Fault Type	Fault Locatio n(km)	θ (deg)	δ (deg)	R_f 0 (Ω)		R_f 5 (Ω)		R_f 10 (Ω)	
				Operation Time (ms)					
				DFT	ANN	DFT	ANN	DFT	ANN
AG	20	30	10	11	11	12	12	18	20
AG	20	30	-10	11	11	12	12	16	19
ABG	40	270	10	14	14	15	15	-	22
ABG	40	270	-10	14	14	23	23	-	23
CG	65	90	-5	16	17	21	23	-	27
CG	65	90	5	16	18	20	23	-	27
BC	75	60	5	21	22				
BC	75	60	-5	21	23				
ACC	77	210	5	23	24	30	33	-	29
ACG	77	210	-5	23	22	26	29	-	30
AG	79	90	5	20	24	-	28	-	32
AG	79	90	-5	21	23	26	31	-	31
CG	80	60	10	21	26	-	30	-	31
CG	80	60	-10	21	25	25	31	-	33
AC	81	210	5	22	-				
CG	82	210	10	23	-	-	-	-	-
ABG	82	90	10	-	-				
ACG	90	90	5	-	-	-	-	-	-

B. Additional Performance Studies

The 6-bus model of the Khorasan province transmission network in Iran is chosen for additional testing of the proposed distance relay. The single-line diagram of this system is shown in Figure 6, with the relay installed on bus S responding to faults in the line ST. Different faults are simulated on transmission lines ST and TD and fault data are generated using EMTDC. The voltages and currents are recorded at bus S. Instantaneous values of the voltage and current signals at bus S are recorded using a sampling frequency of 20 kHz. The recorded fault data are passed through the pre-processing stages described earlier to generate input patterns, which are then presented to the proposed distance relay. Tables 4 and 5 show the outputs of the proposed distance relay for fault resistances of 0 Ω and 8 Ω, respectively. In these tables, operation time of the relay has been indicated.

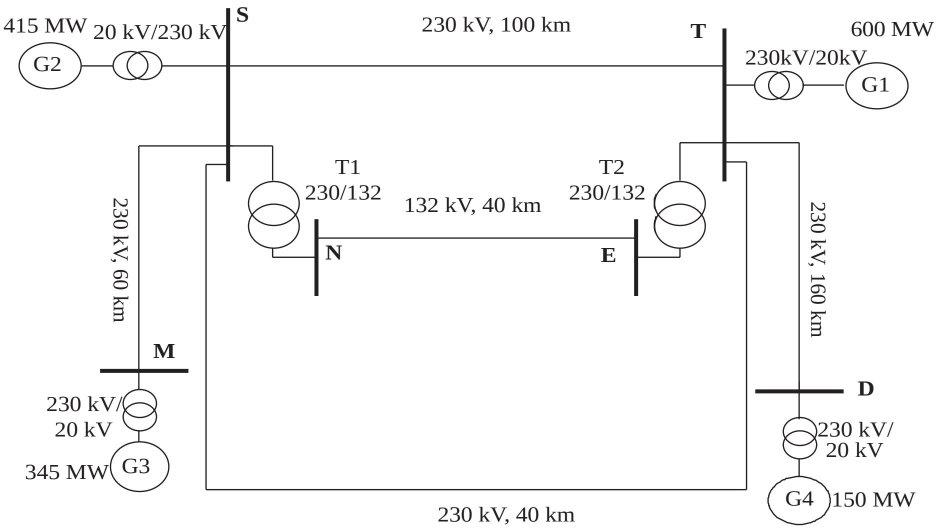

Figure 6. A single-line diagram of the 6-bus model of the Khorasan province transmission network.

Performance of the ANN approach for the faults close to the boundary zone is discussed as follows. As shown in Table 4, the ANN approach performed accurately and reliably for the faults at 78 km, to which the conventional distance relay cannot respond. The ANN-based approach does not encounter the problem of improper action, even for the case where the fault resistance is 8 Ω. As shown in the Tables, the ANN approach has also correctly distinguished faults at 79 km inside the protection zone. As expected, the ANN approach does not operate for the faults outside of the protection zone. These results show that the proposed distance relay performs correctly for a different system.

Table 4. Distance relay test results for faults in the network shown in Figure 6 with $R_f = 0$.

Fault type	θ (deg)	δ (deg)	Fault in ST line		Fault in DT line	
			Operation time (ms)			
			Fault Location (km)	ANN	Fault Location (km)	ANN
AG	0	-10	45	16	8	–
BG	10	10	53	17	10	-
ABG	70	5	63	18	12	–
ABG	90	-5	67	17	22	–
CG	0	-10	74	16	43	–
ACG	120	10	78	17	84	–
CBG	90	10	79	19	95	–
BCG	70	-5	83	–	103	–

C. Discussions

Compared to conventional approaches, the proposed approach has the following advantages:

Wide ranges of tests have been performed using the proposed approach and encouraging results were obtained. The effect of changing different fault factors and system parameters in wide ranges has been considered in the test cases.

The performance of the proposed approach has been checked for faults close to the boundary of the protection zone, including a considerable amount of fault resistance. The proposed relay operates correctly, even for these fault cases, which is better than conventional approaches.

Table 5. Distance relay test results for faults in the network shown in Figure 6 with $R_f = 25$.

Fault type	θ (deg)	δ (deg)	Fault in ST line		Fault in DT line	
			Operation time (ms)			
			Fault Location (km)	ANN	Fault Location (km)	ANN
ABG	30	10	60	17	10	–
AG	30	-10	65	16	20	-
BG	270	10	70	18	30	–
CG	270	-10	72	15	60	–
CBG	90	-5	76	15	70	–
AC	90	5	78	19	90	–
BC	210	-10	79	17	100	–
ACG	70	10	84	–	110	–

The proposed approach has been tested for faults, both inside as well as outside of the protected zone, and correct responses for both cases were obtained. For the faults beyond the first zone, but very close to the protection zone boundary, the relay does not operate as expected.

It is shown that the proposed approach improves distance relay performance for faults close to the protection zone boundary. The zone reach could be increased due to higher selectivity.

8. Conclusion

The use of ANN as a pattern classifier to improve distance relay is investigated in this paper. The results obtained from the proposed approach are very encouraging. The ANN-based relay can provide a precise operation and keep its reach accuracy when facing different fault conditions, as well as network changes. This is an improvement in performance compared to conventional distance relays. Thus, the use of ANNs can extend the first zone reach of distance relays and enhance system security.

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