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Review Article

An Overview of Transmission Line Protection by Artificial Neural Network: Fault Detection, Fault Classification, Fault Location, and Fault Direction Discrimination

Anamika Yadav and Yajnaseni Dash

Department of Electrical Engineering, National Institute of Technology, Raipur 492010, India

Correspondence should be addressed to Anamika Yadav; ayadav.ele@nitrr.ac.in

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Contemporary power systems are associated with serious issues of faults on high voltage transmission lines. Instant isolation of fault is necessary to maintain the system stability. Protective relay utilizes current and voltage signals to detect, classify, and locate the fault in transmission line. A trip signal will be sent by the relay to a circuit breaker with the purpose of disconnecting the faulted line from the rest of the system in case of a disturbance for maintaining the stability of the remaining healthy system. This paper focuses on the studies of fault detection, fault classification, fault location, fault phase selection, and fault direction discrimination by using artificial neural networks approach. Artificial neural networks are valuable for power system applications as they can be trained with offline data. Efforts have been made in this study to incorporate and review approximately all important techniques and philosophies of transmission line protection reported in the literature till June 2014. This comprehensive and exhaustive survey will reduce the difficulty of new researchers to evaluate different ANN based techniques with a set of references of all concerned contributions.

1. Introduction

There is no fault-free system and it is neither practical nor economical to build a fault-free system. The various cases of abnormal circumstances such as natural events, physical accidents, equipment failure, and misoperation generate faults in the power system. The consequences of faults are traumatic amplification of current flow, increasing heat produced in the conductors leading to the major cause of damage. The actual magnitude of fault depends on resistance to flow and varied impedance between the fault and the source of power supply. Total impedance comprises of fault resistance, resistance and reactance of line conductors, impedance of transformer, reactance of the circuit, and impedance of generating station. The conventional distance relay settings are based on a predetermined network configuration with worst fault outcomes [1–6]. As the neural network based algorithm has more adaptability and is likely to be more accurate, various researchers used it for power system protection which is the main focus of this study. A number of prime purposes and applications of ANN are accessible in the literatures; those will assist to recognize the perception of accepting it as a tool for fault detection, classification, and localization on transmission line of the power systems. Various journals, conference papers, books, online libraries, and databases were researched and reviewed for gathering proper information to develop a broad insight and comprehension of the subject being studied. Both scholarly and nonscholarly articles were surveyed and considered from databases like IEEE, Scopus, Google Scholar, Academia Search Premier, Pro-Quest, EBSCO, and other relevant websites.

The paper is organized as follows. In Sections 2 and 3, a brief introduction of power system faults and artificial neural networks is provided, Section 4 is about distance protection by ANN method; in Section 5, ANN and its application for protecting transmission line are illustrated. Section 6 deals with the conclusions drawn from this survey followed by acknowledgments and references.

2. Faults in Power System

Fault is an unwanted short circuit condition that occurs either between two phases of wires or between a phase of wire and ground. Short circuit is the most risky fault type as flow of heavy currents can cause overheating or create mechanical forces which may damage equipments and other elements of power system [1–6].

2.1. Categories of Faults. Faults also can be classified into three types, that is, symmetrical faults, unsymmetrical faults, and open circuit faults.

2.1.1. Symmetrical Faults. The fault that results in symmetrical fault currents (i.e., equal currents with 120 displacements) is known as a symmetrical fault. Three-phase fault is an example of symmetrical fault where all three phases are short circuited with or without involving the ground.

2.1.2. Unsymmetrical Faults. Examples of different unsymmetrical faults are single phase to ground, two phases to ground, and phase to phase short circuits. The details of these shunt fault types that can occur in transmission line are described as follows.

(1) Single Phase to Ground (L-G) Fault. L-G is a short circuit between any one of phase conductors and earth (prevalence is 70%–80%). It may be caused either by insulation failure between a phase conductor and earth or breaking and falling of phase conductor to the ground.

(2) Two Phases to Ground (L-L-G) Fault. L-L-G is a short circuit between any two phases and earth (prevalence is 10%–17%).

(3) Phase to Phase (L-L) Fault. L-L is a short circuit between any two phases of the system (prevalence is 8%–10%).

(4) Three-Phase (L-L-L) Fault. L-L-L is a short circuit between any two phases of the system (prevalence is 2%-3%).

2.2. Open Circuit Faults. This type of fault is caused by breaking of conducting path. Such fault occurs when one or more phases of conductor break or a cable joint/jumper (at the tension tower location) on an overhead line fails. Such situations may also arise when circuit breakers or isolators open but fail to close in one or more phases. During the open circuit of one of the two phases, unbalanced current flows in the system, thereby heating rotating machines. Protective schemes must be provided to deal with such abnormal conditions.

3. Artificial Neural Network

Artificial neural network (ANN) has been equipped with distinctiveness of parallel processing, nonlinear mapping, associative memory, and offline and online learning abilities. The wide uses of ANN with its conquering outcomes make it an effective diagnostic mean in electric power systems. Its versatility with multitude applicability can be seen in other areas of science and engineering research [7–9]. It is a complex network of interconnected neurons where firing of electrical pulses via its connections leads to information propagation. ANN is trained by using prior chosen fault samples as input and set of fault information as output for fault diagnosis application. Neural networks are comprised of primarily three basic learning algorithms such as supervised learning, unsupervised learning, and reinforced learning. Among these supervised learning is most commonly used and is also referred to as learning with a teacher. This is applied when the target is having identified value and is associated with each input in the training set [7]. Figure 1 represents the supervised architecture of ANN.

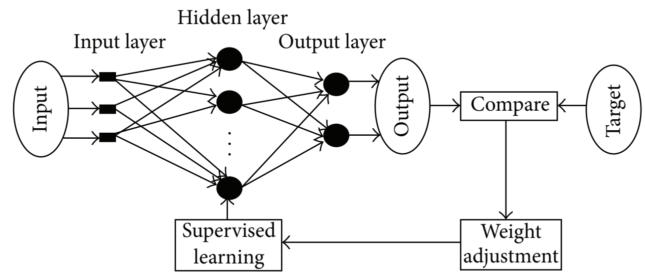

Figure 1: Supervised architecture of ANN.

Error back propagation (BP) neural network was applied by Chan [10] for diagnosis of fault in power system. However slow speed training and the shortcomings of local optima lead to the introduction of additional momentum factor for problem solving. Radial basis function (RBF) neural network has a faster learning speed and the ability of arbitrary function approximation. Bi et al. presented a novel RBF neural network for estimating section of fault. Their simulation results of 4-bus test system shown that the capability of RBF neural network in grid fault diagnosis was better than the conventional BP neural net [11].

For solving improper problems, neural network topologies are to be altered and there is a need to retrain the network. Cardoso et al. [12] used the true capacity of multilayer perception (MLP) and generalized regression neural network (GRNN) for fault estimation in electric power system. GRNN is having the advantage of faster learning, global optimum, and lower requirement of comprehensive sample. They fed the failure information into MLP and the resultant outcome was given as output to GRNN. They also compared ANN fault diagnosis methods with expert system diagnostic methods and found that ANN based methods may evade the formation of expertise, expert heuristic knowledge, and expression and hence save tedious work.

4. Distance Protection by ANN

The fundamental principle of distance protection is that the apparent impedance seen by the relay reduces considerably in case of line fault. A fault is indicated if the ratio of apparent impedance to the positive sequence impedance is less than unity. This scheme of protection is inherently directional and used by impedance and Mho relays. This paper focuses upon the studies of distance protection scheme applying ANN approach.

Adaptive relaying was introduced for widespread applications including incorrect or fault operations measurement. The learning capacity of ANN from input and output patterns extended its applicability in several adaptive protection schemes. Khaparde et al. [13] applied adaline neural network model in offline mode for protective relaying operation of transmission lines. They also proposed adaptive distance protection by using ANN [14]. They have applied MLP model to reduce misoperation of a relay. Girgis et al. [15] presented a method for the computation of fault location in two- and three-terminal high voltage lines which is based on digital computation of the three-phase current and voltage 60/50 Hz phasors at the line terminals. For evaluation of the convergence and distinctive solution, this method was tested by electromagnetic transient (EMPT) generated transient data from a steady state fault analysis. Qi et al. [16] proposed ANN approach for distance protection of power system by taking trained data from simulation of a simple power system under load and fault conditions. According to them conventional distance relays might not function properly under certain conditions such as nonlinear arc resistance, high impedance fault, and variable source impedance. However if such relays are implemented with ANN, such issues can be addressed. Khaparde [17] again proposed an adaptive scheme of distance protection using an artificial neural network. Lai [18] implemented an adaptive protection scheme by ANN approach for classification purpose. They have considered conditions of high impedance fault (hard detection because of minute fault current) and variable source impedance. Coury and Jorge [19] proposed distance protection using ANN for transmission lines utilizing the magnitudes of three-phase voltage and current phasors as inputs. ANN based approach for improving the speed of a differential equation based distance relaying algorithm was developed by Cho et al. [20]. Several researchers illustrated various methodologies for improvements in fault distance computation [21–25].

Venkatesan and Balamurugan [26] developed neural network simulator for identifying the optimum ANN structure necessary to train the data and implement the ANN in hardware. However there is no precise rule for selection of the number of hidden layers and neurons per hidden layer. So it is not certain whether or not the ANN based relay gives the optimum output, for maintaining the integrity of the boundaries of the relay characteristics. Pradhan et al. [27] proposed a high speed distance relaying scheme based on RBF neural network due to its capability of distinguishing faults with data falling outside the training pattern. A sequential procedure for distance protection using a minimal RBF neural network for determining the optimum number of neurons in the hidden layer without resorting to trial and error was illustrated by Dash et al. [28]. Authors [29] trained multilayer feed-forward architecture with two inputs and three-trip or no-trip output signals based approach and used BP technique for three-zone distance protection of transmission lines. The first output was used for main protection of the transmission line section, whereas the other two outputs provide backup protection for the adjacent line sections. The input features extracted by discrete-Fourier transform from the fundamental frequency voltage and current magnitudes.

Santos and Senger [30] developed and implemented of a unique ANN based algorithm for transmission lines distance protection. Their algorithm can be used in any transmission line despite of its configuration or voltage level and also does not require any topology adaptation or parameters adjustment when applied to varied electrical systems. Vaidya and Venikar [31] illustrated an ANN based distance protection scheme for long transmission lines by considering the effect of fault resistance of single line to ground fault type. They have utilized the magnitudes of resistance and reactance as inputs for classifying unknown patterns. A novel distance protection approach for detection and classification stages based on cumulants and neural networks was developed by Carvalho et al. [32].

5. Application of ANN on Transmission Line Protection

This section presents the studies on application of ANN for fault detection, classification, location, direction discrimination, and faulty phase selection on transmission line.

5.1. Studies on "Fault Detection and Classification". It is necessary to identify the fault and classify its type with the aim of establishing safety and stability of the power system. Lim and Shoureshi [33] developed ANN based monitoring system for health assessment of electric transmission lines. Their system showed satisfactory performance in fault classification by using both MLP (multilayer perceptron) and ART (adaptive resonance theory) classifiers. A comparative study of different ANN based fault detection and classification schemes [34–66] is given in Table 1 highlighting the methods used, their response time, and ANN features along with its accuracy.

5.2. Studies on "Fault Detection and Classification and Location". It is extremely essential to identify and locate the transmission line faults for maintaining the proficient and trustworthy operation of power systems. For estimation of the fault location, there are a number of mathematical and intelligent methods accessible in the literature. However, the broad variations in operating conditions such as system loading level, fault inception instance, fault resistance and dc offset, and harmonics contents in the transient signal of the faulty transmission line give rise to unsatisfactory results.

Amjady [67] diagnosed on line power systems fault by a new expert system. Their diagnostic system can be applicable for single or multiple faults and practically examined with real events on a model power system. Several researches have been carried out to detect, classify, and locate the fault on transmission lines by using neural networks by Oleskovicz et al. [68], Coury et al. [69], Othman et al. [70], Mahanty and Dutta Gupta [71], Gracia et al. [72], Lin et al. [73], Jain et al. [74], Othman and Amari [75], Gayathri and Kumarappan [76], Tayeb and Rhim [77], Jiang et al. [78, 79], Warlyani et al.

Table 1: Comparative study of ANN based "fault detection and classification" schemes.

Author and year (reference)	Method used	Response time	ANN features	Accuracy
Dalstein and Kulicke, 1995 [34]	ANN architecture and digital signal processing. Simulation program NETOMAC	(i) Average classification time <6 ms (ii) Arcing fault detection time: 25 ms to 70 ms	Training patterns: 2268 fault cases (i) Two hidden layers with (30-20-15-11) (ii) Back propagation training algorithm Test cases: 240	—
Kezunovic and Rikalo, 1996 [35]	Combined supervised and unsupervised neural network with ISODATA clustering algorithm	Fault detection logic: 0.2 ms and fault classification logic: 15 ms	(i) Training patterns: 1189 (ii) 2 kHz sampling rate (iii) ISODATA clustering algorithm based unsupervised neural network (iv) Test cases: 1188	67.93% to 94.36% fault classification rate
Kezunović et al., 1995 [36]	Unsupervised neural network algorithm MINNET using DFR assistance	Fault detection time: 1 cycle	(i) Training patterns: 1200 faults cases (ii) Two hidden layers with (30-20-15-11) (iii) ISODATA clustering algorithm (iv) Test cases: 295	—
Vazquez et al., 1996 [37]	Feed-forward neural network (FFNN)	Fault detection time: 1/2 cycle	(i) Training patterns: 976–1464 faults cases (ii) 960 Hz sampling rate (iii) Single hidden layer network (5-20-1) or (10-20-1)	—
Vazquez et al., 1996 [38]	Feed-forward neural network (FFNN)	1/4–1/2 cycle	(i) Training patterns: 976–1464 fault cases (ii) 960 Hz sampling rate (iii) Single hidden layer network (5-20-1) or (10-20-1)	—
Chowdhury and Wang, 1996 [39]	Kohonen neural network	1 cycle	(i) Training patterns: 414, testing patterns: 206 (ii) Sampling frequency: 6 kHz (iii) Using the fundamental components of currents and voltages (iv) 2-dimensional Kohonen map consisting of 16 neurons	100% accuracy
Chowdhury and Aravena, 1998 [40]	Kohonen network and multiresolution wavelet filter banks	Not mentioned	(i) Unsupervised Kohonen neural network (ii) Daubechies' wavelet of order ten for preprocessing of the voltage and current signals	—
Wang and Keerthipala, 1998 [41]	Fuzzyneuro approach to fault classification	<10 ms	Inputs: symmetrical components in combination with three line currents (i) Combined fuzzy logic and neural network approach	—
Keerthipala et al., 2000 [42]	Fuzzyneuro approach to fault classification	<1 cycle	Three line current and symmetrical components of currents used as input to fuzzyneuro based protective relay using a real-time digital simulator	—
Vasilic and Kezunovic, 2005 [43]	Fuzzy ART neural network algorithm: fuzzy K-nearest neighbor classifier	1/2 cycle–1 cycle	(i) Sampling frequency: 1.92 kHz and 3.84 kHz (ii) Training patterns: 3315 (iii) Testing patterns: 5000	—
Zhang and Kexunovic, 2005 [44]	Fuzzy ART neural networks	1 cycle	(i) Sampling frequency: 1.92 Hz (ii) NN1 for fault detection, NN2 for fault classification, and NN3 for ground identification (iii) Training patterns: NN1-9564, NN2-9240, NN3-1152. (iv) Testing patterns: 6000	—

Table 1: Continued.

Author and year (reference)	Method used	Response time	ANN features	Accuracy
Silva et al., 2006 [45]	Fault detection and classification using oscillographic data by ANN and wavelet transform	—	(i) Multilayer perceptron (MLP) Daubechies 4 (db4)-ANN architecture (40-30-4) (ii) Training algorithm: RPROP with 426 iterations and rms error is 0.02 (iii) Sampling frequency: 1200 Hz (iv) Fault type: LG, LL, LLG, and LLL Test cases: 720	(i) Fault classification accuracy: 99.83%
He et al., 2006 [46]	Wavelet entropy measure	1 cycle	Wavelet entropy distributing along time to detect the transient fault by comparing with threshold or using ANN classifier	—
Martín et al., 2008 [47]	Combined wavelet and ANN	1/4 cycle	(i) Sampling frequency: 1.92 Hz (ii) Current signals preprocessed using Mallat algorithm for DWT (Daubechies 6) (iii) ANN based fault classification (24-24-7)	—
Kawady et al., 2008 [48]	A Gabor transform-ANN based fault detector	1 cycle	(i) Sampling frequency: 6.4 kHz, GT as a feature extractor and artificial neural networks for pattern recognition and classification (64-10-2) (ii) Test cases: 300	—
Mahmood et al., 2008 [49]	Wavelet multiresolution analysis and perceptron neural networks	—	(i) Sampling frequency: 20 kHz (ii) Daubechies eight (db 8): 5th level detail coefficient of current signals (iii) Perceptron neural network (64-3) with hard limit and perceptron learning rule (iv) Identify lightning stroke, switching surge, or fault	—
Geethanjali and Priya, 2009 [50]	Combined wavelet transforms and neural network	—	(i) Daubechies two (db 2): 5th level detail coefficient of current signals, three-layered ANN (16-33-3) (ii) Training: 160 data, test: 20 data	93.89% accuracy
Pothisarn and Ngaopitakkul, 2009 [51]	DWT and back-propagation neural networks	1/4 cycle for fault classification	(i) Sampling rate is 200 kHz, db4 with 1st level detail coefficient and zero sequence components of voltage and current signals (8 inputs) (ii) Training: 760 data, test: 360 data (iii) Two hidden layers ANN (8-8-11-4)	97.22% accuracy
Abdollahi and Seyedtabaii, 2010 [52]	Comparison of Fourier and wavelet transform methods for fault classification	3 cycles	Sampling frequency: 1 kHz Energies of detailed DWT coefficients of 1st and 2nd frequency components of Iabc and Izero are summed together to form inputs (i) Training: 150 data, test: 50 data (ii) Feed-forward BPNN for fault classification	98% accuracy
Jain et al., 2010 [53]	Artificial neural network for intercircuit and cross-country fault	<1 cycle	Sampling frequency is 1 kHz, fundamental components of voltage and current signals as input to feed forward neural network (FFNN) with Levenberg-Marquardt algorithm (9-50-7) (i) Training and testing: 6000 patterns	—

Table 1: Continued.

Author and year (reference)	Method used	Response time	ANN features	Accuracy
Jain et al., 2008 [54]	ANN based fault detector and classifier	<1 cycle	Sampling frequency is 1 kHz, superimposed, zero and negative sequence components of current signals as input to three layers FFNN trained with Trainlm algorithm (10-10-7), test cases: 240	100% accuracy
Jain et al., 2009 [55]	ANN based fault classifier for SLG faults	<1 cycle	Sampling frequency is 1 kHz, fundamental components of voltage and current as input (i) Training: 1840 and testing: 1800 patterns ANN based fault detector and classifier with single hidden layer (9-30-7)	100% accuracy
Jain et al., 2010 [56]	ANN based fault classifier and locator	<1 cycle	Sampling frequency is 1 kHz, fundamental components of voltage and current as input ANN-FC-Kohonen self-organising map ANN-FL-FFNN (Bayesian regularisation algorithm)	—
Yadav, 2012 [57]	Comparison of single and modular ANN based fault detector and classifier	<1 cycle	Sampling frequency is 1 kHz, fundamental components of three voltage and six currents of double circuit line as input to ANN Training patterns: 8800, testing patterns: 2400 Single ANN (9-50-7), modular fault typewise: ANN LG (9-30-7), LL (9-30-7), LLG (9-8-7), and LLL 9-20-7 Trainlm algorithm	(i) 98% accuracy (ii) Detects/classifies intercircuit, cross-country and evolving faults
Jain, 2013 [58]	ANN based fault detection for transmission lines	<1/4 cycle	(i) Sampling frequency is 1 kHz, fundamental components of three voltages and three currents as input to ANN. Single ANN (6-10-10-1), Trainlm algorithm (ii) Training patterns: 29123, testing patterns: 26912	(i) 100% accuracy
Chen and Aggarwal, 2012 [59]	Wavelet transform and artificial intelligence	1-cycle data (20 samples)	(i) Sampling rate 16 kHz, spectral energy details of 10-level DB wavelet coefficients of 3-phase current as input (30) to ANN (30-20-4)	—
Ben Hessine et al., 2014 [60]	Artificial neural networks	1 cycle	(i) Sampling frequency: 1 kHz, fundamental and zero sequence components of three voltages and three currents as input to ANN FD (8-16-1), (ii) 4 fault classifiers: ANN-R (8-5-1), ANN-S (8-5-1), ANN-T (8-5-1), and ANN-G (8-6-1)	—
He et al., 2014 [61]	A rough membership neural network approach for fault classification		(i) Sampling rate is 50 kHz, wavelet energy of three-phase currents and zero sequence current as input to RMNN (13-14-1) 10 separate RMNNs for 10 types of fault Test cases: 60	Average success classification rate of 99.4%
Koley et al., 2011 [62]	ANN for detection and classification of faults on six-phase transmission line	<1 cycle	Sampling by 1.2 kHz, fundamental components of six-phase voltages and currents (i) Training patterns: 1460 (ii) ANN (Trainlm algorithm) (12-40-7)	—
Koley et al., 2012 [63]	ANN for six-phase to ground fault detection and classification of transmission line	<1 cycle	(i) Sampling by 1.2 kHz, fundamental components of six-phase currents, Training patterns: 370 (ii) ANN (trained with trainlm) (6-3-7)	—

Table 1: Continued.

Author and year (reference)	Method used	Response time	ANN features	Accuracy
Koley et al., 2012 [64]	ANN for phase to phase fault detection and classification of six-phase transmission line	<1 cycle	(i) Sampling by 1.2 kHz, fundamental components of six-phase voltages and currents (ii) Training patterns: 4850 (iii) ANN model (12-30-6), Trainlm algorithm	—
Koley et al., 2014 [65]	ANN based protection scheme for shunt faults in six-phase transmission line	<1 cycle	Sampling by 1.2 kHz, fundamental components of six-phase voltages and currents (i) Total 22 modular ANN modules for fault detection/classification and distance location (ii) Testing cases: 4930 (iii) Trainlm algorithm	100% accuracy Fault location error ±0.73%
Kumar et al., 2014 [66]	Haar wavelet and ANN based phase to phase fault classification in six-phase transmission line	—	Sampling by 1.2 kHz, standard deviation of approximated Haar wavelet coefficients of six-phase voltage and currents as input (i) Training patterns: 1220 (ii) Testing patterns: 100 (iii) ANN model (12-5-6) trained with Trainlm	—

Table 2: Comparative study of ANN based "fault detection and classification and location" schemes.

Author and year (reference)	Method used	Response time	ANN features	Remark(s)
Oleskovicz et al., 2001 [68]	Multilayered backpropagation neural network for fault detection, classification, and location	(i) Average is 13 ms (ii) Classification module: 4 ms to 9 ms (iii) Location module: 8 ms–15 ms	(i) Multilayer perceptron with hyperbolic tangent activation function and supervised BP algorithm with Norm-Cum-Delta learning rule (ii) *Sampling frequency:* 1 kHz, test cases: 405 (iii) Fault detection module (ANN1 24-9-2) (iv) Fault classification module (ANN2 24-16-4) (v) Fault location module (ANN3 24-48-44-3, ANN4 24-44-40-3, ANN5 24-44-40-3, or ANN6 24-24-20-3)	The reach for protection zones 1, 2, and 3 is set at 95%, 130%, and 150% of the protected transmission lines, respectively. (i) Accuracy: 98% (ii) Error: 2%
Coury et al., 2002 [69]	Modular ANN approach for fault detection, classification, and location	*ANN1:* 2 ms detection time *ANN2:* 4 to 12 ms time to classify *ANN3*, *ANN4*, and *ANN5* location time (8 to 15 ms) This scheme can operate in an average time of about 13 ms	(i) Modular ANN approach with hyperbolic tangent transfer function (ii) Learning rate: 0.01 to 0.4 (iii) Momentum: 0.001 to 0.2 intervals (iv) *Sampling frequency:* 1 kHz, test cases: 405 (v) *Fault detection module:* (ANN1 24-9-2) (vi) *Fault classification module* (ANN2 24-16-4) (vii) *Fault location module:* (ANN3 24-48-44-3, ANN4 24-42-40-3, or ANN5 24-24-20-3)	Fault classification accuracy is 99.44%. ANN relay estimated the expected response in approximately 98% of the 4,050 patterns tested. An extension of the relay primary protection zone to 95% of the line length was implemented
Othman et al., 2004 [70]	To detect fault using MRA wavelet transforms, three classifiers are used, namely, GRNN, PNN, and ANFIS The integral square error and multiple objective functions are used as a fitness function during the minimization operation	—	(i) *Feed-forward NN:* BFGS (quasi-Newton BP) is the training algorithm to classify the location of the fault (ii) *GRNN:* wavelet coefficient level 5 as input (iii) *PNN:* wavelet coefficient level 5 for length line of 5 percent increment as an input. (iv) *ANFIS:* 2 inputs and 1 output with 40 membership functions (v) *Coefficients are range influence:0.05, accept ratio: 0.5, squash factor: 1.25, and reject ratio: 0.15*	GRNN and PNN: 100% accuracy when used as fault classifier *Fault location*: *PNN:* 100% accuracy. If noise increased to 0.2% accuracy becomes 85% *GRNN:* 87% accuracy, but addition of 0.02% noise makes it 67.5% *Feed-forward NN:* 47.5% *ANFIS:* 82.5% correct classification
Mahanty and Dutta Gupta, 2004 [71]	Radial basis function network (RBFN) with Gaussian transfer function was used for fault classification and location	—	(i) ANN based fault classification: only samples of three-phase currents as input (ii) *Fault location:* samples of both voltages and currents of the three phases as input (iii) Training for fault classifier: 120 data sets *Fault location:* ANN-I (for faults occurring beyond 50% of line) and ANN-II (for faults occurring within 50% of line)	Fault locator: error goal of 0.001 was considered The analysis result showed that the proposed system has good accuracy and validity

Table 2: Continued.

Author and year (reference)	Method used	Response time	ANN features	Remark(s)
Gracia et al., 2005 [72]	SARENEUR software tool was employed. An AMD Athlon 900 MHz computer with 128 Mb RAM was used to obtain the times. For each line, a total of 23028 cases were verified. These cases correspond to faults simulated for the three phases, in 101 positions with 76 different fault resistances. Several faults provided by the Spanish utility IBERDROLA S.A. were analyzed	—	*Fault location:* ANN has two hidden layers (8 to 9 neurons in 1st layer and 4 to 6 in the 2nd layer). There was no activation function in input layer, but LLP, LTP, TLP, or TTP activation functions were chosen in the output layer. The training time of ANN was always less than 3 min.	No classification error was found in single lines and the error was less than 1% in double circuit lines *Mean error*: *Fault location:* varies between 0.015% and 0.4% *Fault resistance estimation:* varies between 0.017% and 0.46%
Lin et al., 2007 [73]	Distributed and hierarchical NN (DHNN) system was implicated in this study, comprising IDNN and FLNN. IDNN (fault identification NN for detection and classification)	—	FLNN (fault location NN) for four fault classes (LG, LL, LLG, and LLL). (i) 7744 fault patterns. The output of fault location is processed through fuzzy technique which serves as control for accurate fault location. (ii) The location of FLNN has Emax = 0.754 kM and average absolute error Emean = 0.2946 kM.	The study highlighted the utility of DHNN in identification and location of fault. It was evident from this study that location results were not influenced by fault sites, the intermediate resistances, the fault incidence angles, the opposite system impedance, and the phasor angles between EMF of the two systems
Jain et al., 2009 [74]	Back propagation algorithm and Levenberg-Marquardt algorithm	Faults are detected and classified within a quarter-cycle	(i) Only current signals measured at local end have been used to detect and classify the faults in the double circuit transmission line. (ii) *Training patterns:* (1) *Fault type*: A1G and A2G (2) *Fault location*, Lf (km): 0, 10, 20, 30, . . ., 80 and 90 km (3) $\Phi_i = 0$ and 90 deg (4) $R_f = 0\,\Omega$, $50\,\Omega$, and $100\,\Omega$ (iii) *ANN architecture*: 10-10-7 with mse of $5.22565e-07$	Performance of the protection technique has been illustrated with reference to only a single-phase-earth fault as this is the most frequently occurring fault (over 90% of all faults) in transmission networks
Othman and Amari, 2008 [75]	MRA wavelet transform (Daubechies 5) and probabilistic neural network (PNN). The model power system considered for the analysis is using Kundur's four-machine two-area test system	—	PNN was used as the fault classifier (i) *Fault type*: one-phase fault. The designed algorithm was then run with the sigma equals to 0.01 and succeeded in obtaining 100% accuracy using both the training and test data.	*Effect of noise addition on accuracy in PNN*: 110 km *line:* 0.1% noise → 100% Acc 0.2% noise → 97.14% Acc 0.5% noise → 92.38% Acc 30 km *line*: 0.1% noise → 100% Acc 0.2% noise → 100% Acc 0.5% noise → 92% Acc

Table 2: Continued.

Author and year (reference)	Method used	Response time	ANN features	Remark(s)
Gayathri and Kumarappan, 2010 [76]	Radial basis function (RBF) based SVM and scaled conjugate gradient (SCALCG) used	—	It is a hybrid approach having two steps. *Step 1:* RBF based SVMestimates the initial distance of fault using the positive sequence voltages and currents of faulty phases. *Step 2:* Improving the final estimation of thisdistance using SCALCG based neural network with the high frequency range characteristics.	The maximum error of fault location was limited to 1.93 km in the worst case and 0.0001 km in the best case with the short duration of time in each 150 km line
Tayeb and Rhim, 2011 [77]	BP neural networks	—	(i) NeuroShell2 software was used to provide BP neural networks with structures as 6-5-5-3, 6-6-6-3, 6-7-6-3, and 6-5-4-3 (ii) Input layer is linear while at hidden layer and output layer is logistic function. (iii) BP network with two hidden layers	BP neural network architecture is an alternative method for fault detection, classification, and isolation/location in a transmission line system
Jiang et al., 2011 [78, 79]	A hybrid framework involving fault detection, classification, and location using SVMs and adaptive structural neural network (ASNN)	The detection of fault was performed in around 0.0005 s and one-cycle time period was needed to identify and locate the fault	(i) Fault samples: 240000 (ii) Positive, negative, and zero sequences as inputs (iii) SVMs and ASNNs (6 ASNNs each having 50 neurons). After fault detection, a multilevel wavelet transform was applied and features were obtained by PCA	Average detection accuracy of 99.9%, sensitivity and specificity for fault classification of 99.78% and 99.87%, respectively; and average fault location error of 0.47%
Warlyani et al., 2011 [80]	ANN for fault classification and fault distance location using Levenberg-Marquardt training algorithm	Fault is detected and classified within one cycle	(i) 220 KV Teed transmission circuit. Training cases (1) *Fault type:* ABG, BCG, and CAG (2) *Fault location*: in step of 10 km in each section (3) Φ_i: 0° and 90° (4) R_f: 0, 50, and 100 Ω (ii) *Sampling frequency*: 1 kHz-2nd-order low-pass Butterworth filter with cut-off frequency of 400 Hz (iii) mse goal reached at $1.09385e-027$	The proposed algorithm used the voltage and current signals of each section measured at one end of Teed circuit to detect and classify double line to ground faults (i) Automatic determination of faulted types and phases after one cycle from the inception of fault was achieved (ii) Algorithm eliminates the effect of varying fault location, fault inception angle, and fault resistance

Table 2: Continued.

Author and year (reference)	Method used	Response time	ANN features	Remark(s)
Yadav et al., 2012 [81]	An accurate fault classification and distance location algorithm for Teed transmission circuit based on ANN	The algorithm provides automatic determination of fault type, faulty phases, and fault distance location after one cycle from the inception of fault	(i) Levenberg-Marquardt training algorithm (ii) Mean square error goal reached 0.001 (1) Fault type: LG, LL, LLG, and LLLG (2) Fault location in step of 10 km in each section (3) Φ_i: 0° and 90° (4) $R_f = 0\,\Omega$, $50\,\Omega$, and $100\,\Omega$ (iii) Three-layered ANN with 18-13-7 architecture	(i) The errors in locating the fault are in the range of −0.7% to +1.92%. (ii) The proposed scheme allows the protection engineers to increase the reach setting (i.e., a greater portion of line length can be protected)
Teklic et al., 2013 [82]	ANN for fault distance location using Levenberg-Marquardt training algorithm	—	Levenberg-Marquardt (Trainlm) optimization technique for training of ANN based FL Training: 80% Validation: 10% Testing: 10% (24 data sets considered in testing)	*Mean value of percentage error:* fault location: 6.6%; fault resistance: 4.3% In most of the cases the error percentage to locate fault and to estimate resistance was less than 10 %
Jamil et al., 2014 [83]	Combined wavelet transform and generalized neural network for fault location	—	(i) MRA based on DWT (Db4) for capturing the transient characteristics of the fault current signal (ii) R_f: 10 to 1000 and $R_g = 1$ to 10, Φ_i: 36°, 54°, 90°, and 180° (iii) *Sampling frequency:* 100 kHz	*Mean value of absolute relative error:* Wavelet-GNN: around 2%, Wavelet-ANN: around 3% GNN model is more accurate than ANN

Table 3: Comparative study of ANN based “fault direction discrimination” schemes.

Author and year (reference)	Method used	Response time	ANN features	Remark(s)
Sidhu et al. (1995) [87]	Multilayered feed-forward neural network (MLP)	2.4 ms	(i) Three-layer MLP with sigmoid transfer function (ii) Training dataset: 3240 (iii) *Preprocessing*: samples were processed by 4th-order low-pass antialiasing filters at 24 kHz and were resampled at 1.2 kHz with 100 Hz cut-off frequency (iv) ANN based discriminator was implemented on a TMS320C30 based system	The direction determination was not affected by the type of fault, phases involved, power flow conditions, location of the fault, variation in source impedances, the presence of fault resistance, and missing data samples
Sanaye-Pasand and Malik (1996, 1997) [88, 89]	Back propagation (BP) and Marquardt-Levenberg (ML) learning algorithm were compared and ML was chosen because of the reduced network error	—	(i) A bandpass 2nd-order Butterworth filter with 60 Hz passband, three-phase voltage and current sampled at 1.2 kHz (20 samples/cycle) (ii) 30 inputs, two hidden layers (10, 5) of neurons and one output (iii) A new smaller network with 20 inputs, two hidden layers with (10, 5) needs 30% less number of epochs to reduce the error to 5% of its initial value [88] and to 15% in [89]	(i) Authors found that the new 20-input network performed better than the earlier 30-input network (ii) Here, real world fault data had been recorded by Alberta Power Ltd. on the 240 kV transmission systems [89]
Sanaye-Pasand and Malik (1998) [90]	Elman network for fault direction estimation	0 ms–12 ms	(i) Elman network is a two-layer feed-forward network with the addition of a recurrent connection from the output of the hidden layer to its input (ii) The network outputs which fall above 0.5 and below −0.5 are interpreted as forward and backward faults, respectively (iii) 12 inputs, 12 hidden neurons, and one output neuron (iv) For both hidden and output layers: tansig function	40 different forward and backward faults at the relay location were applied to the system and the network's performance was investigated; in all cases except one 3 phases to ground fault, the directional module performed correctly
Wang et al. (1997) [91]	Three-layered multilayer feed-forward network with BP algorithm	—	(i) 500 KV, 300 KM transmission line tested under different operating and fault conditions (ii) Sampled at 1.2 kHZ (iii) Three-layered multilayer feed-forward network with BP algorithm (14 inputs and 5 output values) was used (iv) Training patterns: 3172	Directional comparison power line carrier protection based on the ANN was highlighted in this paper
Song et al. (1997) [92]	Combined genetic algorithm and ANN for fault direction of UPFC transmission line	—	(i) *GANN:* employs a feed-forward NN with GA training (ii) Fault patterns: 6000 (iii) The NN is composed of 12 inputs (3-phase voltages and currents with 2 samples data window), 8 hidden neurons, and 4 outputs (roughly indicating fault position) (iv) The population size (each weight contains the number of population) is varied from 20 to 100 (v) The parental bias parameter was set to 1.4 (vi) Mutation probability was set to 0.3 and the crossover probability was set to 0.8	*Disadvantages of BPNN over GANN*: BPNN needs larger training set covering data of various fault conditions (slow and time consuming); GA can be used for weight optimization *Disadvantages of GANN*: GANN training is also a time consuming process as there are a number of populations for each weight; but in this study, the GANN training is off-line, so time consumption does not matter as long as it can achieve better classification *Average misclassification rate:* GANN: 2.35% BPNN: 3.70%

Table 3: Continued.

Author and year (reference)	Method used	Response time	ANN features	Remark(s)
Fernandez and Ghonaim (2002) [93]	Finite impulse response artificial neural network (FIRANN) for fault detection and direction estimation	2.5 to 4.5 ms	(i) Only unfiltered voltage and current signals sampled at 2 kHz as input (ii) *Training patterns*: 50000 fault patterns consist of a prefault cycle (40 samples) and 1.25 postfault cycles (50 samples) (iii) Testing: 100,000 (iv) Temporal back propagation algorithm (v) ANN architecture: (8-45-35-5) (vi) Number of time-delay units: (5, 2, 2); activation function: symmetric sigmoid	The relay is called FIRANN DSDST and is based on FIRANN type; the relay can detect the fault, determine the faulty phase, fault direction, and detect whether the fault is an undervoltage or undercurrent/overcurrent fault
Lahiri et al. (2005) [94]	Modular neural network approach	3 samples	(i) Current samples of three phases and voltage samples as inputs (12) with 100 training patterns. (ii) Six ANNs each with (10-3-1) (iii) Implemented on a DSP TMS320F243 EVM-board with sampling rate of 1 kHz for 50 Hz system	The modular ANN concept reduces task-complexity and eliminates redundant inputs for fault classification
Yadav and Thoke (2011) [95]	ANN with Levenberg-Marquardt (LM) optimization learning algorithm	Less than 1.5 cycles	(i) Voltage and current available at only the local end of line (ii) Training patterns: 1090 (iii) Testing patterns: 1090 (iv) For fault distance location task, 18 inputs and 8 and 7 neurons in hidden layer for FL1 and FL2, respectively, and 1 in the output layer were found to be suitable	(i) The proposed scheme allows increasing the reach setting up to 90% of the line length (ii) It has the operating time of less than 1.5 cycles as it uses the one-cycle DFT (iii) The technique does not require communication link to retrieve the remote end data
Yadav and Swetapadma (2014) [96]	ANN with Levenberg-Marquardt (LM) optimization learning algorithm	Fault detection, direction estimation, and fault classification take less than half-cycle time	(i) Fundamental component of current and voltage signals at one end of line as input (ii) 3 ANNs for fault detection, classification, and direction estimation (iii) ANN based fault detector (9-20-20-1) (iv) Training and testing fault cases 40800	(i) Main advantage of scheme is that reach setting of relay is up to 99% (ii) Not affected by variation of parameters like fault type, fault resistance, fault location, fault inception angle, and so on (iii) Provides primary and backup protection

TABLE 4: Comparative study of ANN based "faulty phase selection" schemes.

Author and year (Ref)	Method used	Response time	ANN features	Remark(s)
Al-Hassawi et al. (1996) [97]	Two-level: (i) ANN-1 for fault type classification and ANN-2 for faulty phase selection for each fault type	1/4 cycle	(i) Feed-forward with 1 hidden layer. *1stlevel:* 60 inputs with 90 neurons in the hidden layer and 4 outputs. *2nd level:* 60 inputs with 30 neurons in the hidden layer and 3 outputs *1st level:* training data extracted from the fault at 40% and 60% distance from the relay, while testing data was from the same fault at 20% *2nd level:* training data extracted from the fault at 20% distance from the relay, while test data at 40% location	Authors used single circuit 500 kV study system and 2-level hierarchical neural network for higher learning ability and accuracy
Bo et al. (1997) [98]	Feed-forward multilayer perceptron	—	(i) ANN architecture: (18-12-3) (ii) Hyperbolic tangent function (iii) 6 frequency ranges were chosen for each phase and then converted into six features (iv) *Frequency ranges:* (1) below 16.6 kHz; (2) over the range 16.7–31.3 kHz; (3) over the range 31.4–46.91 rHz; (4) over the range 50–65.6 kHz; (5) over the range 66.7–81.3 kHz; (6) over the range 81.4–100 kHz *Sampling frequency:* 200 kHz	*Advantages*: Information used within the phase selector was based on the fault generated high frequency noise Unlike conventional techniques, this information was not influenced by different systems and fault conditions However it was mainly dependent on the behavior of the nonlinear fault arc
Khorashadi-Zadeh (2004) [99]	Multilayer feed-forward network	Within a quarter-cycle	(i) 6 inputs and 4 outputs and 7 and 4 neurons in the hidden layers (ii) Trained with both BP and Marquardt-Levenberg (ML) algorithms (iii) *Activation function:* Tan-sigmoid function was used for hidden layer neurons and saturated linear function for the output layer	ANN approach could perform well even in the presence of substantial amount of fault resistance for the far end faults
Jain et al. (2006) [100]	ANN based accurate fault phase selector and distance locator	Within a quarter cycle	(i) Fundamental components of current and voltage signals as input (ii) Three-phase current input signals were processed by simple 2nd-order low-pass Butterworth filter with cut-off frequency of 400 Hz. (iii) Hyperbolic tangent function in the hidden layer and purelin in output layer (iv) Bayesian regularization BP training algorithms	For most of the faults on the line, the location module is able to respond with an error less than 0.4 percent
Samantaray and Dash (2008) [101]	SVM based fault phase selection and ground detection for fault type classification	10 ms (half-cycle)	(i) *SVM1 for* fault phase selection: Postfault current and voltage samples for one-fourth cycle (five samples) as input (ii) *SVM2 for* ground detection: zero sequence components of fundamental, third and fifth harmonic components of the postfault current signal (iii) *Sampling frequency*: 1.0 KHz *Data collection:* PCL-208 data acquisition card, which uses 12-bit successive approximation technique for A/D conversion; installed on a PC (P-4) with a driver software routine written in C++ having six I/O channels with input voltage range of +5 V	(i) The test results are compared with those of the radial basis function network (RBF) and were found to be superior with respect to efficiency and speed (ii) The classification test results from SVMs are accurate for simulation model and experimental setup and thus provide fast and robust protection scheme for distance relaying in transmission line

Table 4: Continued.

Author and year (Ref)	Method used	Response time	ANN features	Remark(s)
Kale et al. (2009) [102]	Combination of wavelet transform and neural network trained with Levenberg-Marquardt (LM) algorithm	—	(i) Sums of absolute values of 6th level detail coefficients (Db8) of line currents as inputs (ii) ANN architecture (8-15-7) with set mse goal of $1e-05$ (iii) Hyperbolic tangent-hidden layers and pure linear-output layer (iv) *Type of fault:* LG, LL, LLG, LLL, and cross-country faults; *fault location* (km): 10 to 90 in steps on 10 km; *fault inceptionangle:* 0° to 315° in step of 45° (v) *Fault resistance* (Ω): 0 to 200 in steps of 25 Ω *Sampling frequency:* 12.77 KHz	Their proposed phase selector scheme can correctly identify faulted phase on the double circuit transmission line
Shu et al. (2010) [103]	ANN with BP and Marquardt training (Trainlm) algorithm	Half-cycle	Total 1400 training samples and 200 testing samples (A) *Fault classification*: 3 input, 3 output, and 8 nodes in hidden layer (B) *Fault location*: (i) *Input layer:* first 5 rows of the output of the S-transform with the line model current signals (ii) *Hidden layers:* 2 with 16 nodes each (iii) *Activation function:* tansig function for hidden layer and logsig function for output layer	Both faulty phases and healthy lines produced high frequency components because of mutual coupling, so here, S-transform energy of transient current was used to select faulty phase; ANN nonlinear fitting function was used to locate fault distance based on S-transform extracted transient energy
JianYi et al. (2011) [104]	Multilayer feed-forward network and wavelet transform	1.2 ms	DB4 mother wavelet *Training patterns*: (i) Input layer: 30 inputs (10 level decomposition of 3 phases current components) (ii) Hidden layer: 20 nodes (iii) 4 outputs (a, b, c, and g) (iv) *Sampling frequency:* 16.7 kHz (v) *Fault resistance* (Ω): 2 Ω (vi) *Busbars capacitor*: 0.1 μF (vii) *Fault inception angle*: 0° and 90°, X/R ratio = 100	Effectively classified the faulty phase(s) and healthy phase(s) just requiring 20-sample length window data (1.2 ms) and real-time implementation can be possible
Saravanan and Rathinam (2012) [105]	Fault classification and fault location based on Back propagation algorithm (BPN), radial basis function (RBF) network and cascaded correlation feed-forward network (CFBPN)	—	(i) Sequence components of the fault currents of both sending end and receiving end as input (ii) Input samples of 1000×6 (iii) *Fault type:* LG, LLG, and LLLG (iv) FFBPN architecture (1-2-1)	Among all the ANN modules, results of RBF network were found to be better than the other two networks in terms of accuracy

[80], Yadav et al. [81], Teklic et al. [82], and Jamil et al. [83]. A comparative study of different ANN based fault detection, classification, and location schemes is given in Table 2 highlighting the methods used, their response time, and ANN features along with remarks.

5.3. Studies on "Fault Direction Discrimination". Fault direction estimation on transmission line is very crucial for enhancing the performance of power system. Advancement of huge generating stations and highly interconnected power systems entails less fault clearing times. The approach of ANN has been positively utilized for the improvement of many of the standard functions that are operated in transmission lines. The accuracy of an electromechanical, static, or a microprocessor based distance relay is affected by different fault conditions and network configuration changes. Hence the direction of the fault should be discriminated to maintain the normal operation of the power system.

Dalstein et al. have used ANN method to estimate the fault location process by means of directional discrimination. They have proposed a neural network to estimate the direction of the fault [84, 85]. Authors [86] employed neural network for designing two different fault direction discrimination modules for high speed transmission line and found that fault direction can be identified quickly and accurately from their results. Table 3 highlights the different schemes [87–96] used for fault direction estimation with its response time and features of ANN along with remarks.

5.4. Studies on "Faulty Phase Selection". Fault phase selection, an imperative part of fault diagnosis, is carried out by measuring faulty line parameters. Different power system faults such as LG, LL, LLG, LLL, and LLLG on a protected transmission line should be detected, classified, and located and faulty phase should be selected swiftly for performing the normal system operation. The summarized study of different ANN based fault phase selection schemes is given in Table 4 highlighting the methods used, their response time, and ANN features along with remarks [97–105].

6. Conclusion

There are widespread applications of ANN in power system protection, but this paper intensively analyzed few of them. Novel tools and techniques are preferred to maintain power system reliability and security within a satisfactory level for improvement of the performance of digital protective relays, renovation of power industry, and stability of the transmission lines. ANN is found to be robust, accurate, and efficient approach for transmission line fault detection, classification, localization, direction discrimination, and faulty phase selection. A comparative study of different schemes for fault detection, fault classification, fault location, fault direction estimation, and faulty phase selection has been discussed in detail. An extensive survey of the published studies on the subject of ANN application to transmission line protection is specified in this paper which will be beneficial for researchers for further research and development in this field.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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