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A Novel Approach to Fault Classification and Fault Location for Medium Voltage Cables Based on Artificial Neural Network

H. Khorashadi-Zadeh, M. R. Aghaebrahimi

Abstract **-** A novel application of neural network approach to fault classification and fault location of Medium voltage cables is demonstrated in this paper. Different faults on a protected cable should be classified and located correctly. This paper presents the use of neural networks as a pattern classifier algorithm to perform these tasks. The proposed scheme is insensitive to variation of different parameters such as fault type, fault resistance, and fault inception angle. Studies show that the proposed technique is able to offer high accuracy in both of the fault classification and fault location tasks.

Keywords**—**Artificial neural networks, cable, fault location and fault classification.

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I. Introduction

WITH increased environmental concern; there is an increase in demand for underground cables. It is thus very likely that more transmission lines comprising underground cables will be built in the future. This inevitably leads to high demand for accurate cable fault classification and location techniques.

The most commonly used cable fault location method is the pulse-echo technique [1]. This technique uses a high-voltage impulse generator. The application of an impulse generator, to produce the acoustic signal for pinpointing a fault, will almost invariably be successful, provided that the cable is taken out of service. Accurate measurements of the signals produced with the locators are performed using digital transient recorders. The stored data in the recorder can be displayed locally or transmitted to a central location where an experienced operator can interpret the waveforms. The entire process is off-line which cannot be used for on-line classification of the cable fault, not to mention the detection of inception fault or partial discharge.

Protection relaying is just as much a candidate for the application of pattern recognition technique. The majority of power system protection techniques are involved in defining the system state through 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/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 are obtained [2-12].

In this paper an ANN-based approach is used and an accurate fault classifier and locator algorithm is designed. Application of the proposed algorithm reduces the effect of system variables such as fault resistance, fault type, fault inception angle and decaying dc offset. It is shown that the proposed module is able to accurately distinguish cable faults for different system conditions. The proposed algorithm is tested to evaluate its performance in terms of accuracy and robustness. Some of the test results are included in the paper.

II. Simulated System

A 33 kV power system is simulated using EMTDC electromagnetic transient program and various types of faults with different system conditions and parameters are modeled [13]. The one-line diagram of the studied system is shown Fig. 1. Short circuit capacity of the system is considered to be 1 GVA. Source Zo/Z1 ratio and X/R ratio are 1 and 10, respectively. The simulated power system parameters are shown in Table I. The medium voltage cable is simulated using Bergeron model.

Training patterns were generated by simulating different types of faults on the power system. Fault type, fault location, fault resistance and fault inception time were changed to obtain training patterns covering a wide range of different power system conditions. Combination of different fault conditions considered for training pattern data generation is shown in Table II.

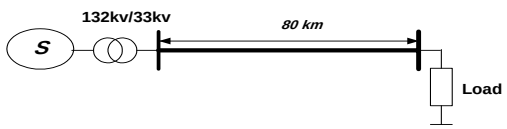


Fig. 1 Simulated system model

TABLE I
SIMULATED POWER SYSTEM PARAMETERS

Positive & Negative Sequence Transformer Impedance (Pu)	J 0.1	
Cable Inductance (H/km)	Pos. Seq.	$1.273.10^{-3}$
	Zero Seq.	$3.82.10^{-3}$
Cable Capacitance (F/km)	Pos. Seq.	373.10^{-9}
	Zero Seq.	197.10^{-9}
Cable Resistance (Ω/km)	Pos. Seq.	0.3
	Zero Seq.	0.9

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TABLE II
TRAINING PATTERNS DATA GENERATION

Fault Type	Single phase to ground, phase to phase to ground, phase to phase, three Phase
Fault Location (km)	Different values between (0-80)
Fault Resistance (Ω)	Different values between (0-10)
Inception Angle (deg)	Different values between (0-360)
Load (MW)	Different values between (1-20)

III. Preprocessing

Preprocessing is a useful method to reduce the dimensionality of the input data set to neural networks. The preprocessing stage can significantly reduce the size of the neural networks based classifiers, which in turn improves the performance and speed of training process [14]. Three phase voltage and current input signals were processed by 2nd-order low-pass Butterworth filters. The anti-aliasing filters had a cut-off frequency of 400 Hz. In addition, 2-sample FIR digital filters were used to remove the dc component.

Magnitudes of the voltage and current signals have been obtained by the full cycle discrete Fourier transform (DFT) filter using voltage and current samples. Patterns were then generated using the processed amplitudes voltages and currents. Obtained patterns are scaled appropriately. The pre-processing configuration of the proposed algorithm is shown in Fig. 2.

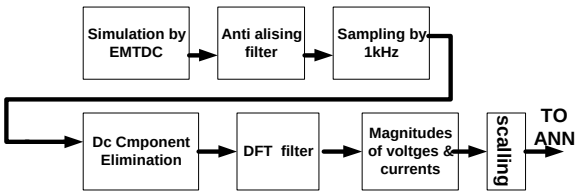


Fig. 2 Pre-processing structure

IV. Proposed ANN for Fault Classification

Multilayer feedforward networks were chosen to process the prepared input data. A few different networks were selected initially. For designing the fault classifier based neural network, different networks with four inputs and four outputs were considered. Four different A, B, C and N outputs were considered to determine whether each of the three phases A, B, C and neutral are present in the fault loop.

The networks' architecture were decided empirically which involved training and testing different number of networks. Three layer networks were found to be appropriate for the fault selector application. For all the networks, hyperbolic tangent function was used as the activation function of the hidden layer neurons. Saturated linear function was used for the output layer [14].

Various networks with different number of neurons in their hidden layer were trained with Marquardt-Levenberg (ML) algorithms [15]. The ML algorithm is a nonlinear least square algorithm applied to learning of the multiplayer perceptions.

Once trained, the networks performance was tested using a validation data set. The suitable network, which showed satisfactory results were finally selected. The selected network structure is shown in Fig. 3. The network has 4 normalized inputs and 4 outputs. The number of neurons for the hidden layer is chosen to be 8 neurons. Based on the fault type, which occurs on the system, output neurons should be 0 or 1. Outputs which are greater than 0.9 are considered to be active and outputs which are smaller than 0.1 are considered to be inactive. Neural network desired outputs for different types of faults are shown in Table III.

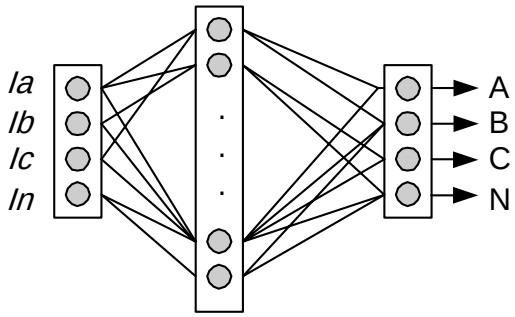


Fig. 3 The proposed network structure

TABLE III
NEURAL NETWORK DESIRED OUTPUTS

Fault Type	A	B	C	N
AG	1	0	0	1
BG	0	1	0	1
CG	0	0	1	1
AB	1	1	0	0
BC	0	1	1	0
AC	1	0	1	0
ABG	1	1	0	1
ACG	1	0	1	1
BCG	0	1	1	1
ABC	1	1	1	0

The proposed network outputs for a single phase CG fault are shown in Fig. 4. For this case, a fault is applied to the system at the time 20 ms and the network outputs are shown for about the first 40 ms after the fault inception, which is of interest. The fault location was 35 km from the relay location. As shown in this figure, the proposed ANN is able to respond to the fault correctly in a timely fashion. The fault is identified just in a few ms, which shows that the ANN is able to detect and classify the fault quit fast. The ANN outputs remain stable after identifying the fault.

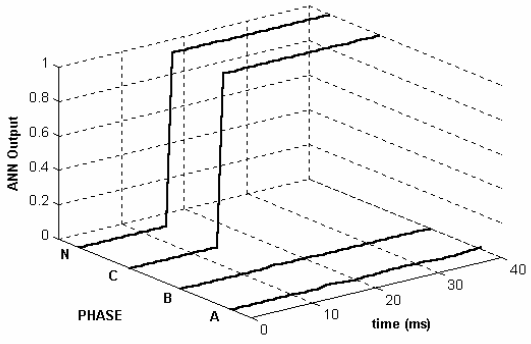


Fig. 4 Outputs of ANN for a fault CG at 35 km

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V. Proposed ANN for Fault Location

A. Basic Structure of the Proposed Algorithm

A neural network–based distance measurement algorithm is proposed as the measurement unit of a fault locator. The block diagram of the proposed fault locator approach is shown in Fig. 5. Most of the necessary information for determining the disturbances and transients in power systems is usually contained in the voltage and current waveforms. Magnitudes of the three phase voltages and currents measured at the relay location are considered as the input data to the algorithm. Voltage and current waveforms are sampled at a rate of 20 samples/cycle.

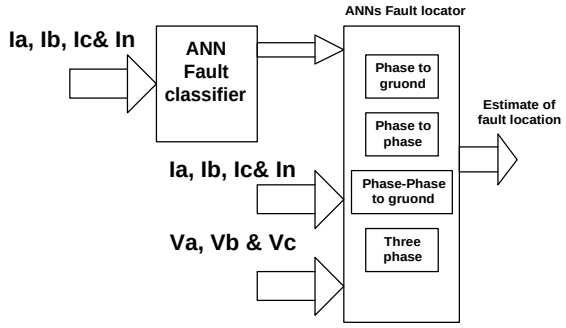


Fig. 5 The proposed relay structure

B. Networks Structure and Training

For the fault locator network, multilayer feedforward networks were also chosen to process the sampled input data. Number of the networks to estimate fault distance was decided by experimentation which involved training and testing of different number of networks. As shown in Fig. 5, four different networks were finally selected to process different fault types, i.e. phase to ground faults, phase to phase to ground faults, phase to phase faults and three phase faults. Based on the fault type, appropriate network is selected and activated by the fault classifier.

Appropriate inputs to each of the networks are also selected by the fault classification module. For example, in case of phase A to ground fault AG, magnitudes of phase A voltage and current and magnitude of neutral current are switched to the first network, the phase to ground network. This network therefore should have 3 inputs. In the case of a phase B to ground fault, magnitudes of phase B voltage and current and magnitude of neutral current are selected as the first network inputs.

For a phase to phase to ground fault, e.g. phase A to phase B to ground fault ABG, two of the phases are involved in the fault. Magnitudes of voltages and currents of both phases A, B and neutral are switched to the appropriate network. Therefore, the phase to phase to ground neural network has 5 inputs. Similarly, the phase to phase and three phase networks should have 4 and 6 inputs, respectively.

For each of the four above-mentioned neural networks, a few different network structures with appropriate number of neurons in their hidden layers were considered. Different networks with one and two hidden layers were considered and trained. It was found that the networks with reasonable number of neurons in their only hidden layers couldn't cover some of the extreme cases. On the other hand, networks with two hidden layers provided better results without having to have high number of neurons in their only hidden layers. The suitable networks which showed satisfactory results and were finally selected are shown in Table IV. A single neuron output layer was chosen for each of the networks. If a fault is located in the cable length, the network target output should be fault distance.

For all the networks, Hyperbolic tangent function is used as the activation function of the hidden layer neurons. Linear function is used as the output layer activation function. Various networks considered were trained with Marquardt-Levenberg (ML) training algorithms.

Once trained, the networks performance was tested using test patterns that were different from the training patterns. Some of the simulation results are presented in the next section.

TABLE IV
STRUCTURE OF THE SELECTED NEURAL NETWORKS

Network Type	Structure
Single phase to Ground	3-7-5-1
Phase to phase to ground	5-8-6-1
Phase to phase	4-5-5-1
Three phase	6-7-3-1

C. Test Results

A validation data set consisting of different fault types was generated using the power system model shown in Fig. 1. The validation set fault patterns were different than the fault patterns used to train the network. For different faults of the validation set, fault type, fault location and fault inception time, were changed to investigate the effects of these factors on the performance of the proposed algorithm. Extreme cases like faults near to the protection zone boundary including fault resistance were also included in the validation data set.

The proposed fault locator result for a few faults with different system conditions is presented in Table V. As an example, test results for a single phase to ground, AG fault at 5 km from the fault locator is presented in the first row of the Table V. For this fault, the load was 10 MW. The fault inception angle with respect to phase A voltage zero crossing was 30 deg.

Module operation results for three different amounts of fault resistance are shown in the last three columns of the table. For the faults, which involved ground, the relay operation result for 0, 4 and 8Ω fault resistance is investigated. For the faults, which do not involve ground, fault resistance is not a critical factor. Therefore, only the module performance without fault resistance is investigated.

As shown in Table V, the proposed module performs quite accurately and reliably. For most of the faults on the cable, the module is able to respond with an error less than 0.2 percent. The module output for a few faults with different power system conditions is presented in this section. The main emphasis is on checking the network's performance under extreme fault cases. In general, the network performs better for more usual fault cases.

TABLE V
OPERATION RESULTS OF THE FAULT LOCATOR

Fault Type	Fault Location (km)	Load (MW)	θ (deg)	R_f 0 (Ω)	R_f 4 (Ω)	R_f 8 (Ω)
				Estimate of distance of faults (km)		
AG	5	10	30	10.01	10.01	10.01
BCG	15	5	90	15.02	15.013	15.016
CG	16	10	180	16.011	16.015	16.021
ABC	18	8	90	18.012		
AC	23	12	216	23.011		
ACG	45	15	30	45.011	45.024	45.013
ABG	49	20	180	49.020	49.011	49.019
BG	51	20	180	51.031	51.021	51.027
CG	58	15	180	58.011	58.032	58.022
ABC	61	20	90	61.013		
AC	64	10	216	64.011		
ABG	67	15	216	67.013	67.017	67.013
BC	69	20	270	69.017		
AB	72	10	30	72.011		
BCG	78	8	60	78.011	78.015	78.016

VI. Conclusions

In this paper an accurate fault classifier and locator algorithm is designed. Neural networks capabilities in pattern recognition and classification are used and two neural network-based modules are designed. Simulation studies are performed and the modules' performance with different system parameters and conditions is investigated. A common problem using conventional fault locator schemes is the distance estimation error. As it is shown by different examples in the paper the proposed fault locator module is more immune to this problem. Different types of faults could be located on the cable with high accuracy using the proposed on-line scheme. Neural networks could be used as a part of a new generation of high speed advanced fault locators.

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