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Neural-Network-Based Fault Location Estimator for Short Medium Voltage Underground Cable

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Abstract: A new application of neural network approach to estimate fault location of short Medium voltage underground cables is demonstrated in this study. Different faults on a protected cable should be classified and location should be estimated. This study presents, the use of neural networks as a pattern classifier algorithm to perform these tasks. The proposed algorithm has a good performance 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 acceptable accuracy in estimation of fault location.

Key words: Artificial Neural Networks (ANNs), underground cable, Fault Place Estimation (FPE) and classification

INTRODUCTION

Electrical energy is being increasingly demanded and many problems result as highly industrialized societies require more reliable energy services. Utilities encounter strong struggles from residents in new electrical systems construction that is due to possible accidental fire; nasty looking resulted from overhead lines and etc….Then using underground cable is necessary and indispensable for such civilized societies. However, it is difficult for underground systems to be well managed; especially their fault identification, classification and location estimation are more difficult than those of overhead lines. In order to minimize such defectives of the underground systems, design and construction for fault detection, classification and location should be optimized. As a result, using pattern recognition techniques are very important to detect and estimate place of faults as soon as possible in these systems. ANNs are powerful in pattern recognition and classification; they possess excellent features such as generalization capability, noise immunity and fault tolerance. Consequently the decision made by ANNs-based fault classification and location estimation will not be seriously affected by variations in system situation. ANN based techniques have been used for power system fault detection and location over the past few years (Chul-H *et al*., 1995; Kezonuic *et al*., 1995; Kezonuic, 1997; Khorashadi-Zadeh and Hosseini, 2004; Sanaye-Pasand and Khorashadi-Zadeh, 2003; Tahar, 2004; Khorashadi-Zadeh and Aghaebrahimi, 2005; Hassan, 2005; Hector *et al*., 1999). In these studies there are several efforts about detection of fault and location by using ANNs. But in general there is a little research on applying ANN techniques for fault detection and location in underground cables.

In this study, ANN-based approach is used and a good performance fault place estimator for short underground cable system is designed. The proposed algorithm which is applied can reduce the effect of system variables such as fault resistance, fault type and fault inception.

ARTIFICIAL NEURAL NETWORKS AND THE LEARNING ALGORITHM

ANNs are based on neurophysical models of human brain cells and their interconnection. Such networks are characterized by exceptional pattern recognition and learning capabilities. Their learning process can be achieved in two steps. First, the network is presented with a set of correct input and output values. Then it adjusts the connection strength among the internal network nodes until the proper transformation is learned. Second the network is presented with only the input data, and then it produces a set of output values. The processing of the input and output data is done several thousand times. After proper number of learning cycles the network will be able to produce output data from input data similar to those used for learning.

ANNs have attracted much attention due to their computational speed and robustness. They have become an alternative to modeling of physical systems such as synchronous machine and transmission line. Most of the applications of ANNs in power system make use of the conventional Multilayer Perception (MLP) model based on back propagation algorithm. Multilayer feed forward can accept several transfer functions, several hidden layers and various neurons in each hidden layer. On the other hand, MLP has a good flexibility during working with that. However, MLP model suffers from slow in learning and the need to guess the number of hidden layers and neurons in each hidden layer. Many improvements are suggested over the conventional MLP to overcome these disadvantages (Sukumar, 1998).

In this study, the fully-connected multilayer feed forward Artificial Neural Network (FFANN) model is chosen to process the input data. Various networks are considered and trained with both conventional Back Propagation (BP) and Marquardt-Levenberg (ML) training algorithms. It was found that networks trained with the ML algorithm provide better results compared with those trained with BP algorithm. ML algorithm is very faster and also very efficient for training networks which made up of a few hundred weights so the computational requirements are much higher. This is especially true when high precision is required, and the necessity of the storage of some matrices that can be quite large for certain problems is needed (Hagan and Menhaj, 1994). Therefore, because of good performance and results, in this study it was decided to use the ML training algorithm for this application.

SIMULATED SYSTEM

A part of Erbil underground distribution system from North of city to Rezgarei substation (33 kV) is modeled by using PSCAD/EMTDC electromagnetic transient program. And also various types of faults with different system conditions are simulated. The one-line diagram of the studied distribution system is shown in Fig. 1. The simulated power system parameters are shown in Table 1. Also the cable configuration is shown in Fig. 2.

The training patterns are generated by simulating the model under different situations. Fault type, fault location, fault resistance, fault inception time are changed in order to obtain training patterns which covering a wide range of different power system conditions. The combination of the different fault conditions which are considered for training and testing process are shown in Table 2.

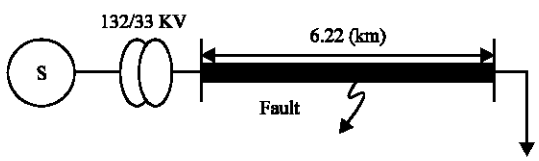

Fig. 1: Simulated system model

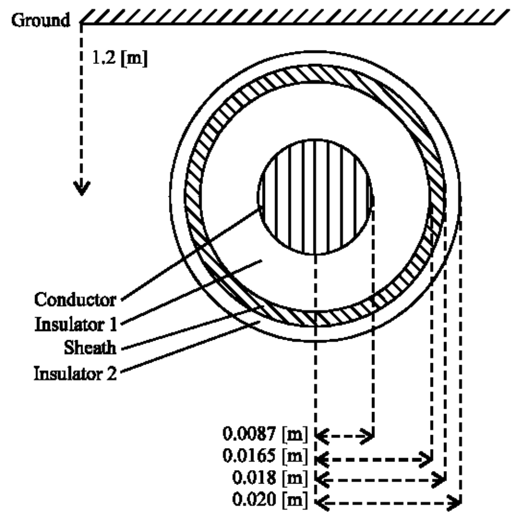

Fig. 2: The cable configuration

Table 1: Simulated power system parameters

Data network	Source impedance	14.01 (Ω)
	Phase angle	84.28°
	Source X/R	10
	Source Z_0/Z_1	1
	Positive and negative sequence impedance of the transformer	J 0. 1
	System frequency	50 (Hz)
	Transient simulation model	Frequency dependence (phase) model
Cable data	Cable length	6.228 (km)
	R_1 = 8 mm (Conductor)	
	Resistivity	$\rho_c = 1.72\times10^{-8}$ [ohm*m]
	Relative permeability	$\mu_c = 1$
	R_2 = 16.5 mm (Insulator 1)	
	Relative permittivity	$\varepsilon_{r1} = 2.7$
	Relative permeability	$\mu_1 = 1$
	R_3 = 18 mm (Sheath)	
	Resistivity	$\rho_s = 2.84\times10^{-8}$ [ohm*m]
	Relative permeability	$\mu_s = 1$
	R_4 = 20 mm (Insulator 2)	
	Relative permittivity	$\varepsilon_{r2} = 2.7$
	Relative permeability	$\mu_2 = 1$
Ground data	Ground resistivity	20 [ohm*m]
	Ground permittivity	0.85
	Earth impedance calculation	Analytical approximation

Table 2: Traning patterns data generation

Fault type	AG, BG, CG, ABG, ACG, BCG, ABCG, AB, AC and BC
Fault location (km)	Different values between (0-6.228)
Fault resistance (Ω)	Different values between (0-10)
Inception angle (deg)	Different values between (0-360)
Load	23.5 (MW)

PREPROCESSING STAGE

In ANNs application, preprocessing is a crucial stage to reduce the dimensions of the input data to the ANNs. This stage can significantly reduce the computational operations which in turn improve the performance and speed of training process (Khorashadi-Zadeh and Aghaebrahimi, 2005). Nowadays several tools, such as Fourier Transform (FT), Short Time Fourier Transform (STFT), Wavelet Transform (WT) and etc…, are used to extract features from the input data. In this study, because FT is more suitable comparing with the other tools; it is selected for analyzing simulated signals. And because of the huge time saving during computation and reduction in number of multiplication in FFT comparing DFT the standard FFT version which is usually available in DSP is applied for our purpose (Ali, 1999). Three phase voltage, current and neutral current (In="3Io"=I_a+I_b+I_c, indicate ground parameter) are processed and their magnitudes at fundamental frequency have been obtained by applying 3 full cycle fault FFT.The input signals first sampled before they are decomposed into harmonics constituents. The task of on-line frequency scanning (FFT) involves a few data processing stages which are;

- Low-Pass Filtering (Anti-Aliasing).
- Sampling (16 samples per cycle) and Fourier Transform.
- Phase and Magnitude Error Correction.

PROPOSED ANN FOR FAULT PLACE ESTIMATION

Basic structure of the proposed algorithm and training: Multilayer feed forward networks are chosen to process the prepared input data. For designing, the fault place estimation, different networks with different input for each

Table 3: Optimized neural networks which are found empirically for each type of fault place estimation

Fault type	No. training cases	No. testing cases	Activation function for hidden and output layers	No. of neuron In each layer	Mean absolute testing error
AG	22	44	Tansig- Purline- Purline	3-6-2-1	0.0671
BG	22	44	Tansig- Purline- Purline	3-4-5-1	0.1089
CG	22	44	Tansig- Purline- Purline	3-4-3-1	0.1078
ABG	22	44	Logsig-Purline-Purline	5-5-3-1	0.0962
ACG	22	44	Tansig- Purline- Purline	5-5-3-1	0.0938
BCG	22	44	Tansig- Purline- Purline	5-6-3-1	0.0877
ABCG	22	44	Tansig- Purline- Purline	6-5-2-1	0.1014
AB	22	44	Tansig- Purline- Purline	4-4-2-1	0.1782
AC	22	44	Tansig- Purline- Purline	4-4-3-1	0.1711
BC	22	44	Tansig- Purline- Purline	4-4-3-1	0.1715

Table 4: Testing result for each type of fault in several fault conditions

Number of fault cases	Fault type	Fault inception angle (Deg)	Load (MW)	Desired output (km)	ANN output (km)		
					Rf = 1(Ω)	Rf = 6(Ω)	Rf = 10(Ω)
1	AG	30	23.5	0.5	0.44985	0.59183	0.61899
2	AG	90	23.5	2.6	2.6535	2.4927	2.4606
3	AG	120	23.5	5.3	5.5146	5.5073	5.5229
4	BG	60	23.5	1.2	1.2264	1.1704	1.1577
5	BG	45	23.5	3.5	3.6397	3.3886	3.359
6	BG	180	23.5	4.8	4.9585	4.7715	4.7604
7	CG	216	23.5	1.8	1.9493	1.6293	1.5683
8	CG	240	23.5	4.2	4.1041	4.0688	4.0871
9	CG	300	23.5	6.2	6.2554	6.2611	6.2361
10	ABG	50	23.5	1.5	1.4167	1.3969	1.3937
11	ABG	150	23.5	2.228	2.0947	2.065	2.0598
12	ABG	250	23.5	3.228	3.3265	3.1366	3.1022
13	ACG	40	23.5	2.5	2.4971	2.3849	2.3395
14	ACG	160	23.5	3.7	3.8162	3.6427	3.5703
15	ACG	270	23.5	5.5	5.6201	5.5052	5.4707
16	BCG	35	23.5	0.728	0.62847	0.74955	0.76931
17	BCG	100	23.5	2.4	2.4852	2.3118	2.2539
18	BCG	220	23.5	5.8	5.8021	5.7937	5.7818
19	ABCG	0	23.5	1.6	1.5447	1.4982	1.4936
20	ABCG	200	23.5	3.2	3.0628	2.9591	2.9526
21	ABCG	350	23.5	4.5	4.4419	4.3719	4.3491
22	AB	70	23.5	1.8	1.4791	1.4843	1.5234
23	AB	140	23.5	3	2.7343	2.9346	3.0068
24	AB	340	23.5	5	4.8455	5.0614	5.0931
25	AC	55	23.5	0.4	0.33742	0.64848	0.63832
26	AC	225	23.5	2	1.6374	1.5604	1.5776
27	AC	325	23.5	5.7	5.7172	5.7284	5.7302
28	BC	0	23.5	2.9	2.7686	2.7540	2.7437
29	BC	45	23.5	4	4.1450	4.0520	4.0417
30	BC	90	23.5	5.228	5.3052	5.2861	5.2770

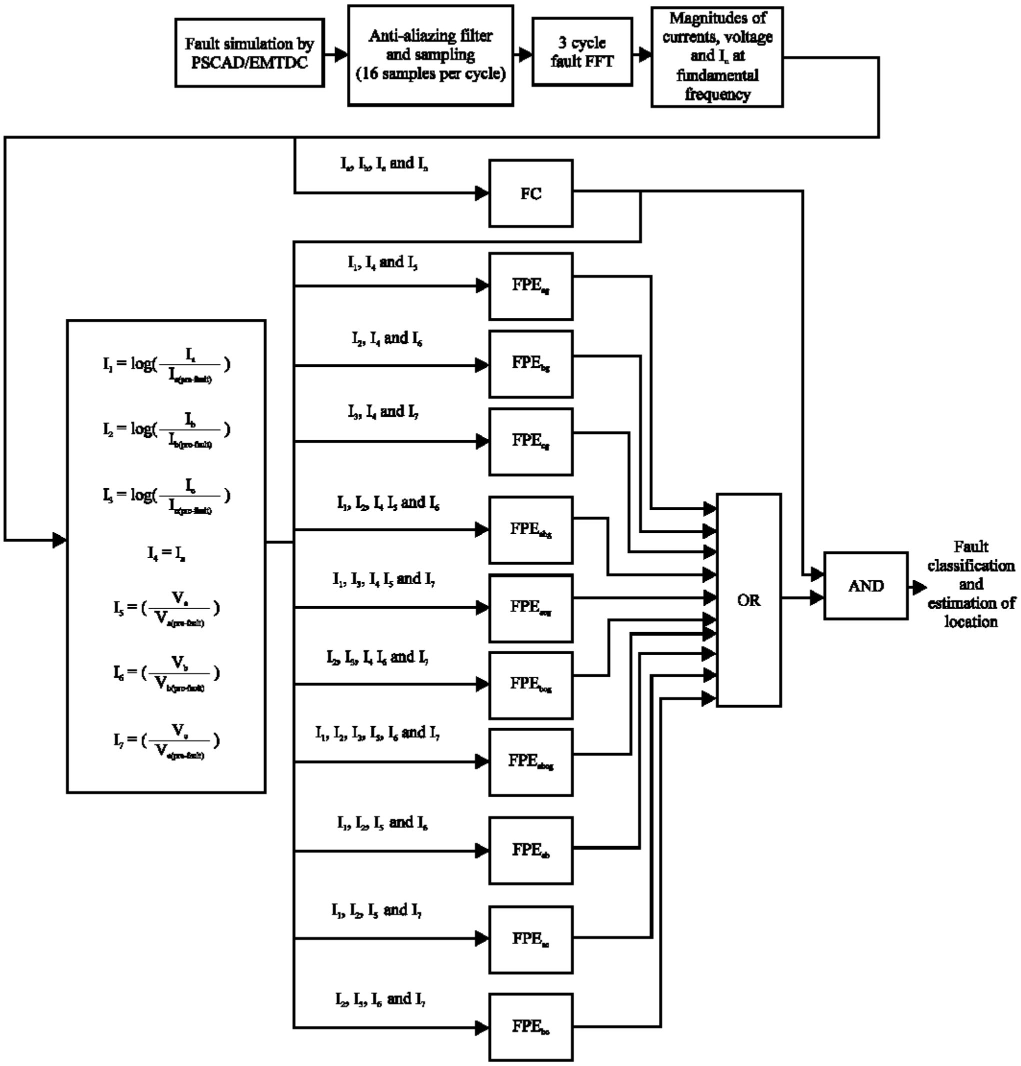

Fig. 3: The proposed algorithm for neural fault classification and fault place estimation with having independent neural networks for different fault loops

type of fault are considered. Ten networks for each 10 type of faults with different hidden layers and different neuron in each hidden layers are investigated. The networks' Architectures were decided empirically by using trail and error method for choosing best ANN structure which is involved to training and testing different number of networks. Unfortunately, it is difficult to know beforehand how large a network should be for a specific application. If a larger network is used the more complex functions of the network can be created and if small enough networks are selected, they will not have enough power to over fit the data. In this study, early stopping method was used for improving network generalization. In which a part of testing fault cases is used for network confirmation and validation. Various networks with different number of neurons in their hidden layers were trained with ML algorithms. The proposed algorithm for fault place estimation is shown in Fig. 3. And also optimized networks to estimate location for each type of fault is given in Table 3.

Test result: A set of data consisting different fault types in different location are generated from the modeled power system. The test data are different from the fault patterns used to train the network. In this study for each type of fault, 22 fault cases for training and 44 fault cases for testing the networks are used. Different fault conditions such as fault type, fault location, fault inception time and fault resistance are changed to investigate the effects of these factors on the performance of the proposed algorithm. Testing result for each type of fault for several fault cases is shown in Table 4.

CONCLUSION

In this research a method that employs neural network for fault classification and location in short radial medium voltage Underground Cable is designed. ANNs capabilities in pattern recognition and classification are used and ANN-based module is designed. Simulation studies are performed and the module's performance with different system parameters and conditions is investigated. It was found that fault place estimation in short underground cable exactly is very difficult. A specific data preprocessing is required to estimate place of fault. And also it was found that finding optimized networks need time and care. A little difference between hidden layers and their neurons with training algorithm can change the result of network completely. Another result which is extracted in this study is , networks trained with the ML algorithm provide better results compared with those trained with BP algorithm. As it is shown by different examples the proposed algorithm has acceptable accuracy and is reliable for all fault cases conditions. On the other hand, if the length of selected cable is divided to 12 zones, the proposed algorithm exactly tell us the zone of each fault which is occurred.

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