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FAULT IDENTIFICATION AND CLASSIFICATION FOR SHORT MEDIUM VOLTAGE UNDERGROUND CABLE BASED ON ARTIFICIAL NEURAL NETWORKS

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This paper presents a fault identification and classification method based on Artificial Neural Networks for medium voltage radial underground cable of Erbil distribution system. It presents the use of Neural Networks as a pattern classifier to perform tasks of different fault identification and classification. The proposed scheme is insensitive to variation of different parameters such as fault type, fault resistance, fault inception angle and load of system. Result show that the proposed technique is able to offer high accuracy in fault classification tasks.

K e y w o r d s: Artificial neural networks, underground cable, fault classification

1 INTRODUCTION

Electrical energy transmission system is being increasingly demanded and many problems result as highly industrialized societies need safer and more reliable energy services. Provider and consumers both experience increasing difficulties from various reasons. Utilities encounter strong resistance form residents in new transmission line construction because of possible accidental fire, nasty looking resulted from overhead transmission lines, and then; underground cable systems are necessary and indispensable for such civilized societies nowadays.

These days the underground system is very important for distribution systems especially in metropolitan cities, city centers, air-port and defense service. The underground system provides a large capacity in transmission and no harm from visual harassment. However, it is difficult for underground system to be well managed; fault identification, classification, location estimation and repair are more difficult than those of overhead transmission systems. In order to minimize such defectives of the faulted underground systems, design and construction should be optimized in that fault detection, classification and also location to become easy and reliable.The underground system requires faster detection and correction of accidental faults along lines for more reliable service. In papers [1–8] there are several works in detection of fault type by using ANN but in this paper ANN-based approach is used and an accurate fault classifier for short underground cable system is designed. Application of the proposed algorithm reduces the effect of system variables such as fault resistance, fault type and fault inception angle. 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.

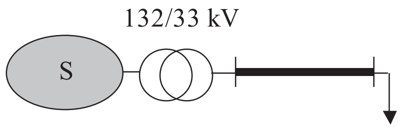

Fig. 1. Simulated system model

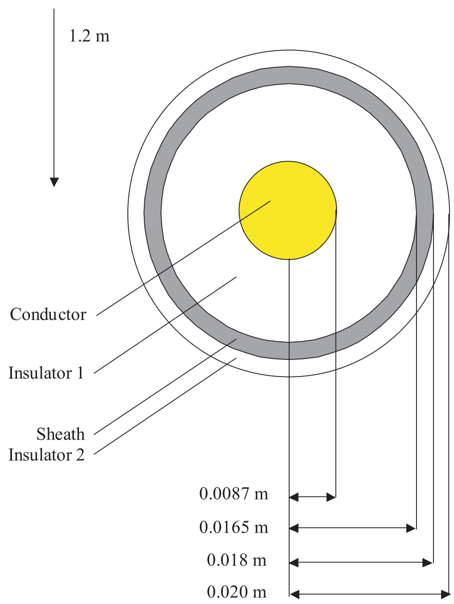

Fig. 2. Cable Configuration

2 ARTIFICIAL NEURAL NETWORKS AND LEARNING ALGORITHM

Neural networks are based on neurophysical models of human brain cells and their interconnection. Such networks are characterized by exceptional pattern recognition and learning capabilities. The major advantage of

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Table 1. Simulated power system parameters.

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

the neural networks is its self-learning capability. 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 proper transformation is learned. Second the network is presented with only the input data, and then it produces a set of output values. The development of the input and output data is done several thousand times. After proper number of learning cycles or iterations the network will be able to produce accurate output data from input data similar to those used for learning.

Artificial Neural Networks (ANNs) have attracted much attention due to their computational speed and robustness. Absence of full information is not a big as a problem in ANNs as it is in the other methodologies. A major advantage of the ANN approach is that the domain knowledge is distributed in manner. Therefore they reach the desired solution efficiently. Most of the applications make use of the conventional multilayer Perception (MLP) model based on back propagation algorithm. Multilayer feedforward can accept several transfer functions, several hidden layers and various neuron in each hidden layer, on the other hand MLP has a good flexibility during working with that , however, multilayer perceptron model suffers from slow learning rate 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 [9].

In this paper, 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. The ML algorithm is a nonlinear least square algorithm applied to the batch learning of multilayer perceptions. It was found that networks trained with the ML algorithm provide better results compared with those trained with BP algorithm [10]. ML algorithm is very faster and also very efficient when training networks which made up to a few hundred weights. Although the computational requirements are much higher for each iteration for the Marquardt algorithm, this is especially true when high precision is required. The main drawback of the Levenberg-Marquardt algorithm is that it requires the storage of some matrices that can be quite large for certain problems [10]. Therefore, because of good performance and results, in this paper it was decided to use the ML training algorithm for this application.

Table 2. Training patterns data generation.

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

3 SIMULATED SYSTEM

A part of Erbil underground power system of 33 kV by using PSCAD/EMTDC electromagnetic transient program is modeled and various types of faults with different system conditions are simulated [11]. The one-line diagram of the studied distribution system is shown in Fig. 1. The power system parameters are shown in Table. 1. also the cable configuration is shown in Fig. 2.

The training patterns are generated by simulating different types of faults on the model power system. Fault type, fault location, fault resistance, fault inception time and system load to be changed in order to obtain training patterns covering a wide range of different power system conditions. Combination of the different fault conditions are considered for training and testing data as shown in Table 2.

4 PREPROCESSING STAGE

In ANN application preprocessing is a useful stage to reduce the dimensionality of the input data to neural networks. This stage can significantly reduce the size of computational operations in the neural networks, which in turn improves the performance and speed of training process [7]. Because of huge time saving during computation and reduction in number of multiplication in FFT compared DFT with the same result; the standard FFT version which is usually available in DSP is applied for our purpose [12]. Three phase voltage, current and ($\boldsymbol{I}_n = 3\boldsymbol{I}_0 = \boldsymbol{I}_a + \boldsymbol{I}_b + \boldsymbol{I}_c$, *indicate ground parameter*) are processed and magnitudes of the voltage and current signals at fundamental frequency have been obtained by applying full cycle Fast Fourier Transform (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.

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

In general for all 2322 fault cases which are simulated by PSCAD/EMTDC before feed to neural network were passed from the preprocessing stage.

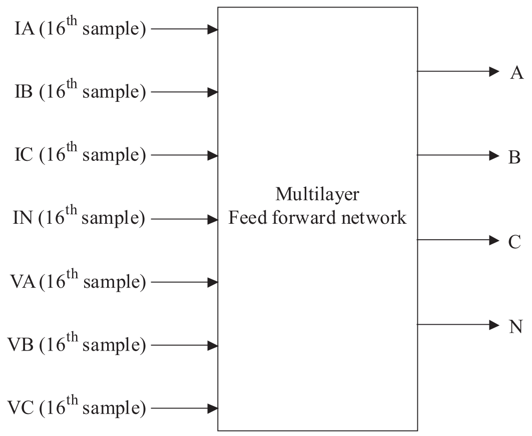

Fig. 3. Proposed Algorithm

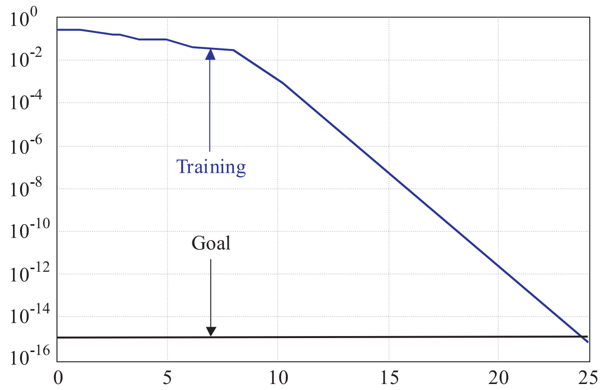

Fig. 4. Learning curve versus epoch point, performance is $6.13375\times 10^{-16)}$, goal is 1×10^{-15}

5 PROPOSED ANN FOR FAULT CLASSIFICATION

5.1 Basic Structure of the proposed Algorithm and training

Multilayer feed forward networks were chosen to process the prepared input data. A few different networks were selected initially. For designing the fault classifier based ANNs, different networks with seven inputs which are 16^{th} sample after fault occurrence for magnitude at fundamental frequency of (I_a, I_b, I_c, V_a, V_b, V_c, I_n) signals and four outputs are 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' 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 used the

Table 3. Neural Network desired and actual output for several fault cases.

Fault Type	Fault Location (km)	Fault Resistance (Ω)	Fault Inception angle (deg)	Load (MW)	ANN Output							
					Desired Output				Actual Output			
					A	B	C	N	A	B	C	N
Normal	[none]	[none]	[none]	23.5	0	0	0	0	0.00998	0.01267	0.01458	0.0038
AG	1.5	8	0	16	1	0	0	1	0.99894	2.97e-05	0.0009	0.99966
BG	2	4	30	12	0	1	0	1	0.00259	0.99997	0.00366	1
CG	2.5	10	120	20	0	0	1	1	0.00295	0.00113	0.99999	0.99909
ABG	3	6	200	10	1	1	0	1	0.99946	0.99973	3.43e-06	0.99954
ACG	3.5	9	150	18	1	0	1	1	0.99917	0.00045	0.99998	0.99992
BCG	4	0	60	21	0	1	1	1	2.78e-05	0.99999	0.99942	0.99999
ABCG	4.5	5	90	15	1	1	1	1	0.99951	0.99832	0.99996	0.99894
AB	5	7	45	13	1	1	0	0	1	1	0.00031	0.00039
AC	6	2	300	8	1	0	1	0	1	0.00052	0.99879	0.00084
BC	5.6	1	180	5	0	1	1	0	0.00013	0.9997	0.99999	9.72e-05
Normal	[none]	[none]	[none]	25	0	0	0	0	0.01316	0.0157	0.01794	0.00542

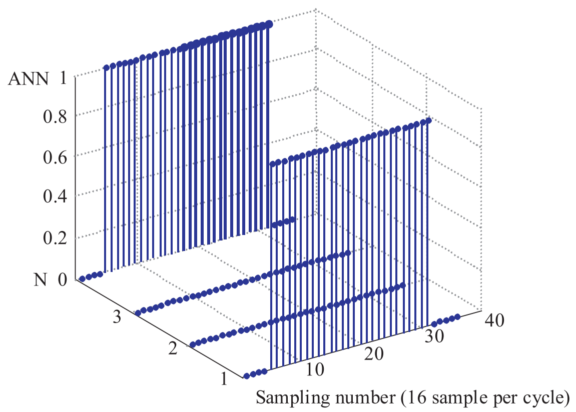

Fig. 5. Output of ANN after rounding for AG fault with $L_f =$ 16 (MW), inception angle=0 (deg), $R_f = 8\,\Omega$ and located at $lf = 1.5$ km (far from recording point) for 40 samples after fault occurrence, 16 samples fault duration and 24 samples after fault interruption.

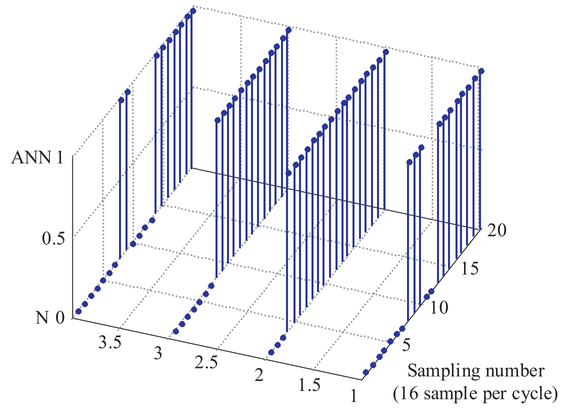

Fig. 6. Output of ANN after rounding for ABCG fault with $L_f =$ 15 (MW), inception angle=0 (deg), $R_f = 10\,\Omega$ and located at $l_f = 4.228$ km for 20 samples after fault occurrence.

more complex the functions the network can create and if we use a small enough network, it will not have enough power to over fit the data. In this paper *early stopping* method was used for improving network generalization in which a part of testing fault cases was used for network confirmation. Finally four layers networks (input, two hidden layers and output) were found to be appropriate for the fault selector application. For all the networks, different functions were used as the activation function of the hidden layers and output layer. The proposed algorithm is shown in Fig. 3.

Various networks with different number of neurons in their hidden layers were trained with Marquardt-Levenberg (ML) algorithms [10]. The network with (7-7-9-4) neurons in input, hidden and output layers with *Tan-Sigmoid* as activation function for hidden layers and *Log-Sigmoid* as activation function for output layer was found to be suitable which showed satisfactory results and was finally selected. The learning curve of the network which is selected is shown in Fig. 4.

5.2 Test result

A test data set consisting of different fault types are generated from the power system model shown in Fig. 1. The test data set are different from the fault patterns used to train the network. In this paper we used 645 fault cases for training and 1677 fault cases for testing the network. Different fault conditions such as fault type, fault location, fault inception time, fault resistance and load are changed to investigate the effects of these factors on the performance of the proposed algorithm. For the selected network which was found by trail and error method total average absolute test error between actual and desired output of ANN for all 1677 fault cases was (8.0276×10^{-4}). As a result we can estimate the accuracy of network is (99.92 %).

The proposed fault classification result for a few faults with different system conditions for both desired and actual output of ANN is presented in Table. 3. Finally all output of ANN is rounded to 1 and 0, it means all data above 0.5 are considered 1 and under 0.5 are rounded to 0.

The actual response of ANN after rounding versus sampling number for two fault cases are shown in Figs. 5 and 6. As shown ANN able to recognize the fault and classify it in less 16^{th} sample which is used for training neural network before and also from Fig. 4, we can see if fault be interrupted the output of ANN going down to has 0 values in its output which is desired.

6 CONCLUSIONS

This work presented a method that employs neural network for fault classification in short radial medium voltage Underground Cable. Neural Networks capabilities in pattern recognition and classification are used and neural network-based module is designed. Simulation studies are performed and the model's performance with different system parameters and conditions is investigated. As it is shown by different examples in the paper the proposed modules is accurate and insensitive to fault type, fault resistance, fault inception angle and system load variation. Therefore, fault classification could be done accurately in different power system conditions. The general accuracy of the proposed scheme is (99.92 %). Having good performance and accuracy, adaptability, easy to use, reliability *etc.* are advantages which cause that ANN be more desired compared the conventional methods for fault classification in underground cable.

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