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Transmission Line Protection Using Artificial Neural Networks

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Abstract: ***Application of neural networks in electrical power systems have demonstrated that this powerful tool can be employed as an alternative method for solving problems accurately and efficiently. In this paper, an artificial neural networks approach is presented for the detection, classification and isolation (location) of transmission line faults occurring in the system of transmission line. The main aim is to implement a complete scheme for distance protection of a transmission line system. In order to perform this goal, the distance protection task is subdivided into different neural network for fault detection, fault identification (classification) as well as fault location in different zones. 110 KV transmission line system is used to create training and testing data for the neural network by mat-lab program. The result show that the neural network is a powerful analysis tool for providing faults information that is more reliable and accurate than provided by the traditional relay.***

Keywords: ANN, FFANN, transmission line, back propagation

1. Introduction

The greatest to the continuity of electricity supply is system faults. Faults on electrical power systems are an unavoidable problem. Hence, a well-coordinated protection system must be provided to detect and isolate faults rapidly so that the damage and disruption caused to the power system is minimized.

The clearing of faults is usually accomplished by device that can sense the fault and quickly react to disconnect the faulty section from healthy ones, in the control centers of the electrical power systems a large number of alarms are received as a result of different types of faults. To protect these systems, the fault must be detected and isolated accurately. The operators in the control centers have deal with a large amount when time is the critical issue, in addition, the protection system may, itself, fail, let alone disruption in the communication networks and corruption of transferred data. All these are challenges to the protection of the electrical power systems. The challenges are detected, classify and locate the faults as possible they occur.

Conventional schemes set threshold according to the fault currents and voltages [1]. When a fault occurs, the fault current and voltages develop a transient DC offset component and high frequency transient component in addition to power frequency components. The fault currents and voltages vary with fault type, location size and fault inception angle and system condition. These variations cause the space to be non-linearly separable and none of the thresholds can be found so as to satisfy for various system and fault conditions [2]. Furthermore, when faults take place, the faulted phase(s) have effect on the healthy (s) due to mutual coupling between these phase(s). This problem is compounded by the fact that this coupling is highly non-linear in nature and is dependent on a complex interplay amongst a number of variables [2].

Intelligent systems have been in use for fault diagnosis in power system for some time [3-4]. Among the intelligent systems, Artificial Neural Networks (ANN). ANN employed as pattern classifiers, has been used in the area of transmission line fault diagnosis [5]. Due to the neural networks ability to acquire information and to learn through training. The capability of neural networks to generalize as well as their fault tolerance makes them a reliable tool to be used to handle unseen fault patterns.

2. Modeling The Transmission Line System

A 110 KV transmission line system studied as a sample which connect ELFAU with GEDAREF (145Km) is used to develop and implement the proposed architectures and algorithms for this problem. "Fig. 1" shows a one-line diagram of the system used to train and test the neural networks. The zones of protection are shown in "Fig. 1", where zone 1 is 50 Km, zone 2 is 100Km and zone 3 is 125Km from substation A respectively. The above power system was simulated using the mat-lab.

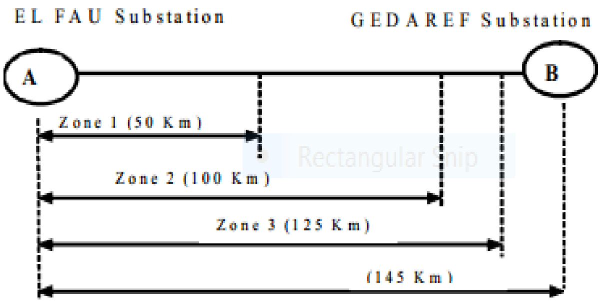

Figure 1: One-line diagram of the system studied

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The three-phase voltages and currents, V = [Va Vb Vc] and I = [Ia Ib Ic] are measured at substation A in figure (). These signals will be utilized subsequently as inputs to the proposed neural networks-based scheme. The Mat-lab Power System Block Set is used to generate the data for the 110-kV transmission line system corresponding to faulty conditions in the subsequent simulation results we consider the following three categories, namely phase to ground faults, phase to phase faults and double-phase to ground faults. The data set required for training the neural networks developed below is generated from various fault situations considering different fault locations for training, validating and generalization purposes more than 200 different fault cases were generated for the detection task, the classification problem and fault location task.

A. Artificial Neural Networks

The Artificial Neural Network (ANN) is considered as a machine like the brain of the human and one of the famous classifiers used in the Electrical Power Systems especially for the fault (Detection, classification and localization). Moreover, there are different types of this network like (Feed Forward (FF), Cascade Forward Back-Prop. (CFB), Radial basis (RB)…etc.). It has the properties of learning, training, capability and generalization [6]. Also, it can be defined as a set of artificial neurons that is depending on a series of a specific mathematical model for information processing on the basis of relational approach for the computation [7]. The most significant property for this algorithm is the ability to understand and learn the behavior of the model with a lot of data training which give satisfy and desirable results because this algorithm deal with the linear and non-linear systems. Therefore, the Feed Forward Artificial Neural Network (FFANN) algorithm was adopted to classify and localize the fault. The ANN can be responded to the changes, but with the small changes, the ANN may not investigate the minor changes of the input signals which might come from the noise or even the distortion to the signal that is lying in this pattern [8]. Therefore the signal that has small distortion or noise, the ANN will not be taken into consideration the small differences In the other hand, this algorithm expects the behavior of the system or the model even without the prior knowledge of this situation or even the behavior because it had been trained for different behaviors before and therefore this algorithm will imply the way that will or want to follow, and all these acquis belong to a lot of training. In case of learning more about each changing might effect on the efficiency of the algorithm particularly when there is an overlapping with the information of the different situation or variables with different behavior.,

B. General Characteristics of the Human Brain (Biological Neuron)

The human nervous system consists of billions of neurons of various types and lengths relevant to their location in the body "Fig. 2" shows a schematic of an oversimplified biological neuron with three major functional units — dendrites, cell body, and axon. The cell body has a nucleus that contains information about heredity traits, and a plasma that holds the molecular equipment used for producing the material needed by the neuron. The dendrites receive signals from other neurons and pass them over to the cell body.

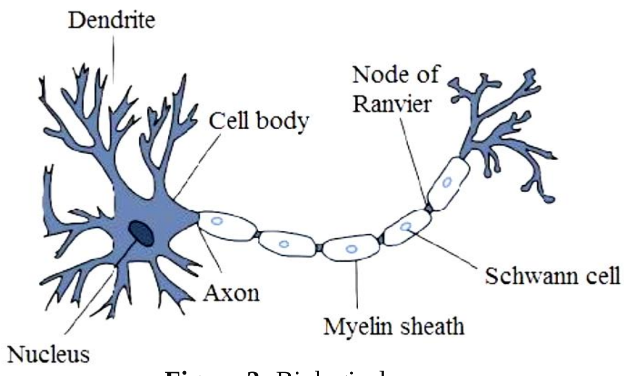

Figure 2: Biological neuron

C. Types of Neural Networks

- MLP network, which is considered a part of multi-layer neural networks. This type of networks doesn't have any feedback.
- Network with feedback, where the output of each neuron, may become a feed back to same neuron or all other neurons.

3. Design Overview

The objectives of this chapter are to design, test and implement a complete methodology for the problem of transmission line system fault diagnosis. As a pre-processing step the training and the testing data generated from the transmission line system are collected. The first step is that of the detection of a fault situation in the system. Following that, fault classification and fault isolation location (zone 1,2 or 3) task are investigated. As stated before, the contribution of thesis is to propose an integrated methodology by utilizing a bank of neural networks to perform these tasks. A back-propagation neural network is used for the fault detection, classification and isolation tasks. In order to convert the instantaneous voltages and current signals to practically constant values, they were transformed to RMS values. The per unit values are used to scale the RMS values of the voltages and currents. The use of the per unit scaling is due to the presence of different nominal values for the voltages and currents measured in volts and amps. To select a characteristic feature fault and to reduce the training set and, therefore, the average values of the voltages and currents during the fault period are used. As an illustration, "TABLE I" shows samples of the voltage and current per unit values used as training set in the normal condition (no fault) as well as the training set subject to various fault types.

In order to train all the proposed networks, the input and output data is applied sequentially. To obtain enough

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examples for training, different types of fault are simulated at different fault locations. Considering these factors, 80 different fault cases for each fault category are used to train the proposed networks.

Table I: Voltage and Current Per Unit

Case N.O	Input Vector (P.U)						Fault Type
	V_a	V_b	V_c	I_a	I_b	I_c	
1	.9972	.9991	.9985	.9978	0.9988	0.9984	No fault
2	0.3335	1.1937	1.1722	3.3345	0.9814	0.9791	A to Ground
3	1.1722	0.3335	1.1937	0.9814	3.3345	0.9791	B to Ground
4	1.1937	1.1722	0.3335	0.9814	0.9791	3.3345	C to Ground
5	0.4713	0.6501	.9856	5.3791	5.3741	0.9834	A to B
6	.9856	0.4713	0.6501	0.9834	5.3791	5.3791	B to C
7	0.4713	.9856	0.6501	5.3791	0.9834	5.3791	A to C
8	0.2045	0.2045	1.1878	7.1872	7.8554	0.9851	A to B to Ground
9	1.1878	0.2045	0.2045	0.9851	7.1872	7.8554	B to C to Ground
10	0.2045	1.1878	0.2045	7.1872	0.9851	7.8554	A to C to Ground

D. Design of neural network for fault detection

In order to design a neural network for addressing the fault detection problem several different topologies of MLP (Multi-Layer Perceptron) neural network are studied. The criteria used to implement and select an appropriate MLP neural network for the problem of fault detection does take into consideration the factors such as the network size of the training data as shown in “Fig. 3” and” Fig. 4”.

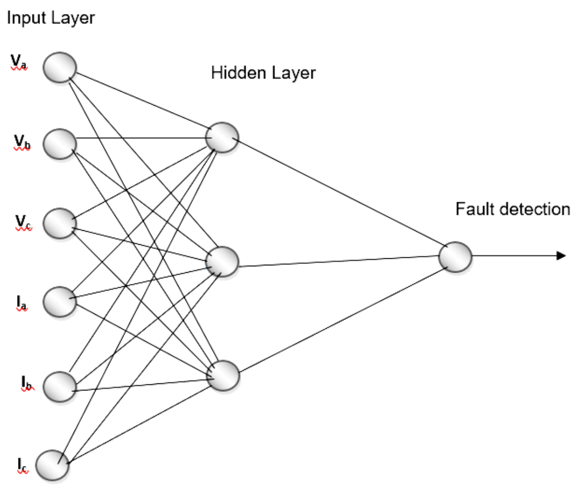

Figure 3: Back Propagation Neural network chosen for fault Detection

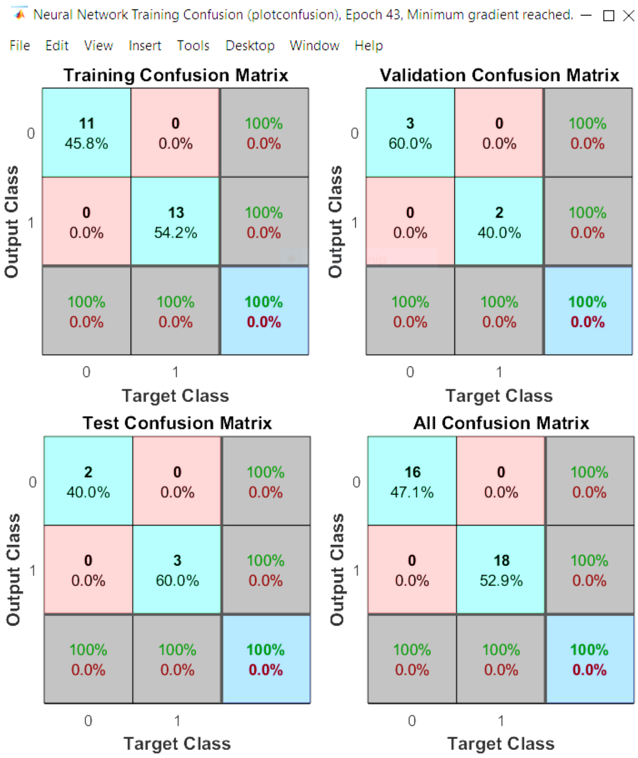

Figure 4: The result of simulation detection and test faults

E. Fault Identification (Classification)

When a fault is detected. The next step is to identify the type of the detected fault. This section presents the results for the design and implementation of a neural network that successfully performs the task of classification of different types of faults detected. The same process that was illustrated in design overview for the design and development of the detection neural network is also followed in this section in order to choose the most suitable BP network as a fault classifier.

The network to be designed here has to have six inputs (the three phase voltages and currents) and four outputs associated with the four fault categories.

The outputs contain variables whose values are given as either 0 or 1 corresponding to the three phases and the ground (that is A, B, C and G) and can be generalized to represent all the practical fault categories permutation involving combinations of phases. The proposed neural networks here

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should classify the specific phases involved in the fault scenario. It should able to distinguish among nine (9) different categories of faults as illustrated in “TABLE II”.

Table II: The BP Classification Network Truth Table

Fault situation	Networks Outputs			
	A	*B*	*C*	*G*
A - G	1	0	0	1
B-G	0	1	0	1
C-G	0	0	1	1
A - B	1	1	0	0
B- C	0	1	1	0
C-A	1	0	1	0
A-B-G	1	1	0	1
B – C – G	0	1	1	1
C – A - G	1	0	1	1

A large number of BP networks with different structures were studied and analyzed in order to obtain the simplest structure with the fastest training time.

After an exhaustive search for the most suitable network size, the one with only one hidden layer and five hidden neurons was chosen to carry out the classification task. The activation function at input layer is linear function while at hidden layer and output layer logistic function. The proposed networks as stated before has six inputs (the three phase voltages and currents) and four outputs. This network is illustrated in “Fig. 5” and “Fig. 6”.

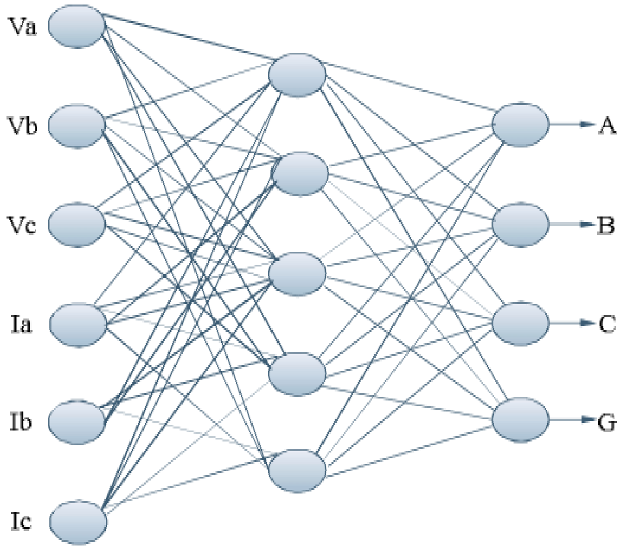

Figure 5: Back Propagation Neural network chosen for fault classification

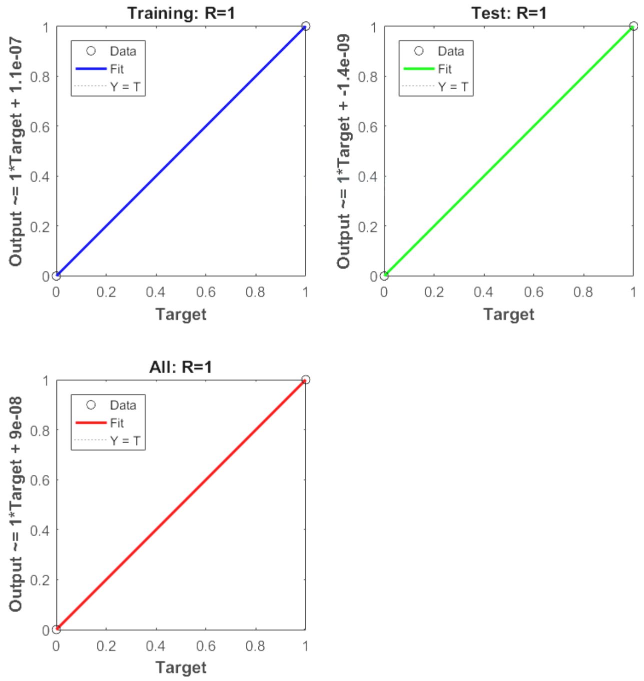

Figure 6: Simulation result of faults classification Network

F. Fault Isolation/ Location (Identifying the Faulty Zone)

Following the detection and classification of the faults, the task of fault isolation Location is performed. In other words, one has to determine the physical location of the fault zones 1, 2 and 3 respectively.

The BP architecture is designed and applied to handle the fault location task. The network is provided with the same number of inputs as in the previous task of fault classification (that is three phase voltages and currents) are now assigned with three outputs corresponding to the three fault zones/ locations (Z1, Z2 and Z3). Different structure for the above network were studied as in the previous section of fault classification. Design of Neural Network for Fault Isolation/ Location The same process that was illustrated in design overview for the design and development of the detection neural network is also followed in this section in order to choose the most suitable BP network as a fault isolator. The network is expected to identify the location of the fault by classifying the identified fault into one of the three fault zones, namely Z1, Z2 and Z3.

The proposed neural networks here should isolate the specific zone involved in the fault. The desired truth table for the network training is shown in “TABLE III”.

Table III: The Isolation Network Desired Response

Fault Location	**Networks Outputs**		
	Z1	***Z2***	***Z3***
Zone 1	1	0	0
Zone 2	0	1	0
Zone 3	0	0	1

It is found experimentally through trial and error that a Bp network with two hidden layers provides the best training performance. The first hidden layer has 5 neurons and the second hidden layer has 4 neurons. The activation function at input layer is linear function while at hidden layer and output

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layer is logistic function. This network is illustrated in "Fig. 7".

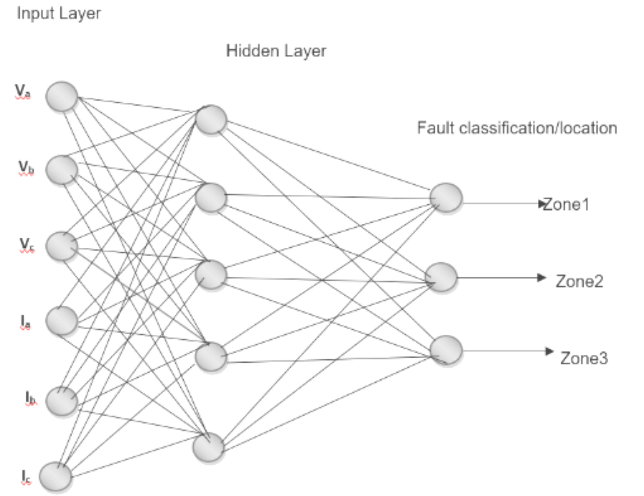

Figure 7: Back Propagation Neural network chosen for fault isolation

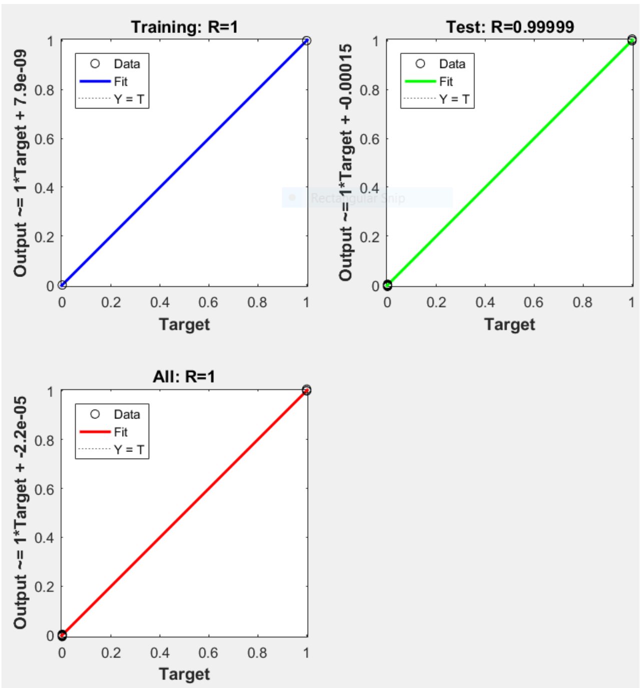

Figure 8: The result of fault isolation Network

4. Conclusion

The back-propagation neural network (BP) architecture has been examined in this thesis and used as an alternative method for fault detection, classification and isolation in transmission line system. It has been shown for all three properties the results obtained demonstrate that in general the performance of the back-propagation neural network (BP) architecture was highly satisfactory.

The software was used to construct simulation models of the transmission line system and as a channel for the generated information is MATLAB (Version 9.0.0.341360) R2016a. Three common faults were discussed; single phase to ground faults, double phase faults and double phase to ground faults. Neural networks do indeed provide a reliable and attractive alternative approach for the development of a protection relaying system for the power transmission systems and can be used for supporting a new generation of high speeds protective relaying systems.

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