Transmission Line Faults Detection, Classification and Location using Artificial Neural Network

Eisa Bashier M. Tayeb Omer A/Aziz A/Rhim

Abstract--**Transmission lines, among the other electrical power system components, suffer from unexpected failures due to various random causes. These failures interrupt the reliability of the operation of the power system. When unpredicted faults occur protective systems are required to prevent the propagation of these faults and safeguard the system against the abnormal operation resulting from them. The functions of these protective systems are to detect and classify faults as well as to determine the location of the faulty line as in the voltage and/or current line magnitudes. Then after the protective relay sends a trip signal to a circuit breaker(s) in order to disconnect (isolate) the faulty line.**

The features of neural networks, such as their ability to learn, generalize and parallel processing, among others, have made their applications for many systems ideal. The use of neural networks as pattern classifiers is among their most common and powerful applications.

This paper presents the use of back-propagation (BP) neural network architecture as an alternative method for fault detection, classification and isolation in a transmission line system. The main goal is the implementation of complete scheme for distance protection of a transmission line system. In order to perform this, the distance protection task is subdivided into different neural networks for fault detection, fault identification (classification) as well as fault location in different zones.

Three common faults were discussed; single phase to ground faults, double phase faults and double phase to ground faults. The result provides a reliable and an attractive alternative approach for the development of a protection relaying system for the power transmission systems.

Index Terms-- **Transmission lines; fault detection; artificial neural network.**

I. INTRODUCTION

THE greatest threat to the continuity of electricity supply is system faults. Faults on electric 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 devices that can sense the fault and quickly react to disconnect the faulty section. It is therefore an everyday fact of life that different types of faults occur on electrical systems, however infrequently, and at random locations. Faults can be broadly classified into two main areas which have been designated as "Active" and "Passive" [1].

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 faults must be detected and isolated accurately. On mainly overhead line systems, the majority of short-circuit faults, typically 80–90%, tend to occur on overhead lines and the rest on substation equipment and busbars combined [2]. The operators in the control centers have to deal with a large amount of data to get the required information about the faults.

The information processing via biological neural networks is done by the huge amount of complex interconnections of the neuronal cells (neurons) which interact among each other by exchanging brief electrical pulses or action potential.

Inspired by the biological nervous system, ANN operates on the principle of largely interconnected simple elements operating as a network function. In doing so, no previous knowledge is assumed, but data, records, measurements, observations are considered. ANN research stands on the fact of learning from data to mimic the biological capability of linear and nonlinear problem solving [3].

Basically, we can design and train the neural networks for solving particular problems which are difficult to solve by the human beings or the conventional computational algorithms. The computational meaning of the training comes down to the adjustments of certain weights which are the key elements of the ANN. This is one of the key differences of the neural network approach to problem solving than conventional computational algorithms which work step-by-step. This adjustment of the weights takes place when the neural network is presented with the input data records and the corresponding target values.

Due to the possibility of training neural networks with off-line data, they are found useful for power system applications. The neural network applications in transmission line protection are mainly concerned with improvements in achieving more effective and efficient fault diagnosis and distance relaying [4].

The goal of this paper is to detect and identify the type of fault in the line and to determine which zone (segment) of the

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line has become faulty. Back-propagation neural network approach is studied, implemented and modified to perform these three tasks. To identify the existence of faults in the system voltage and current signals of a line are observed. These signals are also used to specify the fault type and location.

The simulation models of the transmission line system are constructed and the generated information is then channeled using the software MATLAB (Version 7) and accompanying Power System Block Set (Version 2.1). Besides Neuroshell-2 software used to provides back-propagation neural networks.

II. Transmission Lines Model

The commonly model used for AC overhead transmission lines is called pi model network and is shown in Fig.1. Where shunt admittance has been even divided into two shunt elements connecting to both ends of a pi equivalent network. [5], [6].

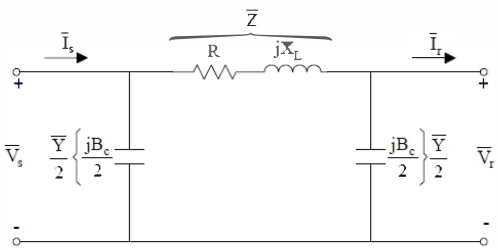

Fig. 1. Π -Network for a Transmission Line Model

A 110 kV transmission line system connects EL FAU with GEDAREF (145 Km) is used to develop and implement the proposed architectures and algorithms for this problem. Fig. 2 shows a single-line diagram of the system used to train and test the neural networks. The system consists of two Substations and (145 Km) transmission line.

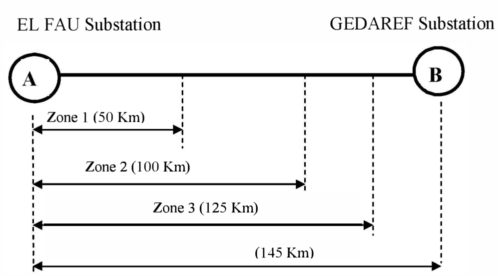

Fig. 2. Single-line diagram of the system studied.

The three-phase voltages and currents, V = [Va Vb Vc] T and I = [Ia Ib Ic] T are measured at substation A in Fig. 2 (4) The simulations presents three categories namely (i) phase to ground faults (ii) phase to phase faults and (iii) double-phase to ground faults.

III. Back Propagation Algorithm

Back Propagation was created by generalizing the Widrow-Hoff learning rule to multiple layer neural networks and nonlinear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors. The term back propagation refers to the manner in which the gradient is computed for nonlinear multilayer neural networks [7].

The output values Oj of a given input pattern Xi do not always correspond to their predetermined value Rj. The error Ej is given by the difference of Rj and Oj and is to be minimized by the weight changes. The error of a neuron j in the output layer is:

$$E_j = \frac{1}{2}(R_j - O_j)^2 \tag{1}$$

The total error E of an output layer is

$$E = \sum_j E_j = \frac{1}{2}\sum_j (R_j - O_j)^2 \tag{2}$$

So, we need to minimize the error E, with respect to the weight changes (ΔW_{ij}). We follow the delta rule to incorporate the learning rate α , along with the gradient descent algorithm techniques to define the weight change,

$$\Delta W_{kj} = -\alpha . \frac{\partial E}{\partial W_{kj}}; \qquad 0 < \alpha \leq 1 \tag{3}$$

If the gradient $\frac{\partial E}{\partial W_{kj}}$ is positive then the weight change should be negative and vice versa. Hence, a minus sign is added at the right hand side of (3). Considering neuron,

$$\Delta W_{kj} = -\alpha . \frac{\partial E}{\partial W_{kj}} \tag{4}$$

Using a sigmoid transfer function $T_j(S)$, the output O_j is defined as:

$$O_j = T_j(S_j) = \frac{1}{1 + e^{-S_j}} \tag{5}$$

For the hidden layer input (H_k) to the output layer,

$$S_j = \sum_k W_{kj} . H_k \tag{6}$$

From (3) and (4),

$$\begin{aligned} \Delta W_{kj} &= -\alpha . \frac{\partial E_j}{\partial W_{kj}} = -\alpha . \frac{\partial E_j}{\partial O_j} . \frac{\partial O_j}{\partial W_{kj}} \\ &= -\alpha . \frac{\partial E_j}{\partial O_j} . \frac{\partial O_j}{\partial S_j} . \frac{\partial S_j}{\partial W_{kj}} \end{aligned} \tag{7}$$

From (1) we get,

$$\frac{E_j}{\partial O_j} = \frac{-2}{2}(R_j - O_j) = -(R_j - O_j) \tag{8}$$

Using (5) we get,

$$\frac{O_j}{\partial S_j} = -O_j(1 - O_j) \tag{9}$$

From (6) we get,

$$\frac{\partial S_j}{\partial W_{kj}} = \frac{\partial(\sum_k W_{kj}.H_k)}{\partial W_{kj}} = H_k \tag{10}$$

Combining (7) to (10), we finally get,

$$\Delta W_{kj} = \alpha.(R_j - O_j).O_j(1-O_j)H_k \tag{11}$$

So, new weights are,

$$W^{`}_{KJ} = W_{kj} + \Delta W_{kj} \tag{12}$$

The error of the output layer is back propagated to the weights of the hidden and the input layer. ΔW_{kj} is the change in weights from the output layer to the hidden layer. The back propagated error E_k of the hidden layer is given by:

$$E_k = \sum_j E_j = \frac{1}{2}\sum_j (R_j - O_j)^2 \tag{13}$$

Corresponding to (2) is the weight change ΔW_{ik}. We introduce a new learning rate $\dot{\alpha}$. We finally get the weight changes in the hidden layer as:

$$\Delta W_{ik} = \alpha'.\sum_j (R_j - O_j).O_j(1-O_j).W_{kj}.H_k(1-H_k)X_i \tag{14}$$

It has been proven that back propagation learning with sufficient hidden layers can approximate any nonlinear function to arbitrary accuracy. This makes back propagation learning neural network a good candidate for signal prediction and system modeling [3].

IV. Artificial Neural Network Design

Artificial neural network is an interconnected group of artificial neurons that uses a mathematical model or computational model for information processing based on a connectionist approach to the computation [1].

Transfer function in the ANN is an important key element to invoke the nonlinear relationships that maps the input(s) to the output(s). Without the transfer function the whole operation is linear and could be solved using linear algebra or similar methods. We consider the transfer function for the weighted sum S (lumped input) of the inputs for a successful network design. In the process of learning the neural network presented with pairs of input and output data then teaches how to produce the output when the corresponding input is presented. When learning is complete, the trained neural network, with the updated optimal weights, should be able to produce the output within desired accuracy corresponding to an input pattern. The learning situations in neural networks can be classified into two distinct sorts. These are supervised learning, and unsupervised learning [4]. 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 (zones 1, 2 or 3) tasks are investigated.

A. Design of Neural Networks for Fault Detection

After extensive simulations of the output error and network output, it was decided that the desired selected network would have an input layer with 6 neurons and one hidden layer with three hidden neurons beside an output layer with one neuron. The activation function at input layer is linear (-1, 1) function while at hidden layer and output layer is logistic function. The selected network is shown in Figure (3) and the performance and error plots associated with this architecture are given by Figures (4) and (5). [8].

Table 1
Voltage And Current Per Unit Values Used As Training Set [8]

Case NO.	Input Vector (P.U)						Fault Type
	Va	Vb	Vc	Ia	Ib	Ic	
1	.9972	.9991	.9985	.9978	.9988	.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	5.3791	0.9834	A to B
6	0.9856	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

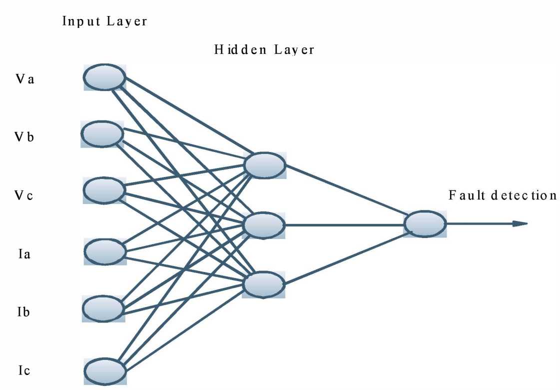

Fig. 3. Back Propagation Neural network used for fault detection.

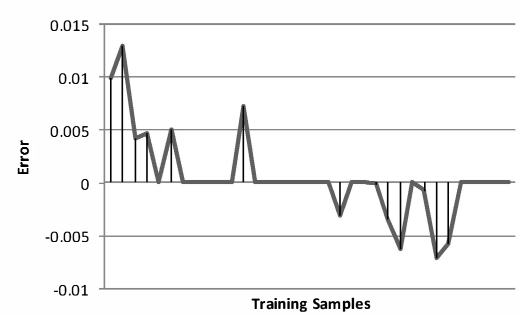

Fig. 4. Output error for the BP neural network 6-3-1

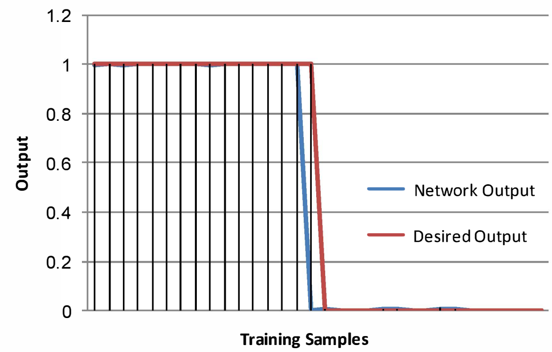

Fig. 5. Network output versus desired output for BP neural network 6-3-1.

A test set was created to analyze the performance of the proposed network. A new set of data will apply to the network that's never seen before. A fault cases for each category of fault were utilized in the test set. Appendix includes the variables considered to form the test set. Error plot of the testing set is shown in figure (6). Performance of network is shown in figure (7).

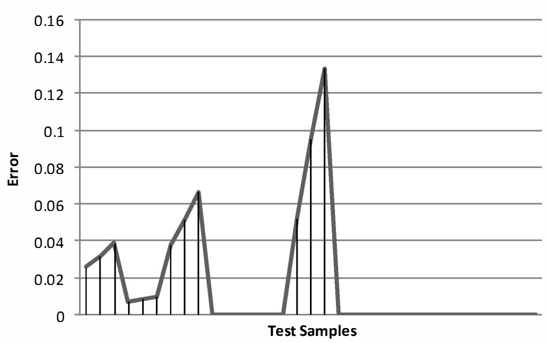

Fig. 6. Testing samples output error for the BP neural network 6-3-1.

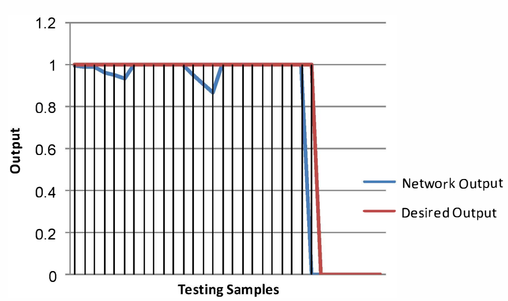

Fig. 7. Testing samples Network output versus desired output for the BP neural network 6-3-1.

B. *Design of Neural Networks for Fault Classification*

The design and development of the uses BP network as a fault classifier. The network designed here has 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 I 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 should classify the specific phases involved in the fault scenario. It should be able to distinguish among nine different categories of faults as illustrated in Table (2).

TABLE 2
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 networks were extensively studied. 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 (-1, 1) function while at hidden layer and output layer is logistic function. The proposed network as stated before has six inputs (the three phase voltages and currents) and four outputs. This network is illustrated in Figure (8).

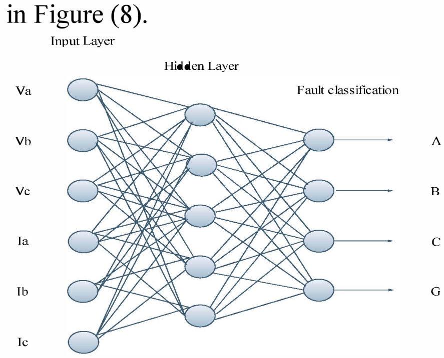

Fig. 8. Back Propagation Neural network chosen for fault classification.

The BP neural network for fault classification was tested using the same test set which was used to test the detection network. A fault cases for each category of fault were utilized in the test. Appendix includes the variables considered to form the test set. Error plot of the testing set is shown in figure (9). The selected network from the previous section was able to recognize correctly the type of the detected fault.

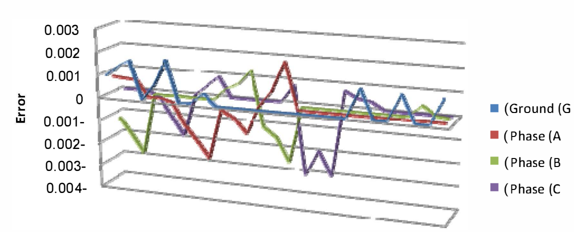

Fig. 9. Testing samples output error for the BP neural network 6-5-4.

C. *Design of Neural Network for Fault Isolation/Location*

The design and development of the detection neural network is 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 (3).

TABLE 3
THE ISOLATION NETWORK DESIRED RESPONSE.

FAULT LOCATION	NETWORKS OUTPUT		
	Z1	Z2	Z3
Zone 1	1	0	0
Zone 2	0	1	0
Zone 3	0	0	1

A large number of BP networks with different structures were studied and analyzed in order to obtain the simplest structure. The training includes some of the selected networks, namely structures, 6-5-5-3, 6-6-6-3, 6-7-6-3 and 6-5-4-3. 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 (-1, 1) function while at hidden layer and output layer is logistic function. This network is illustrated in Figure (10).

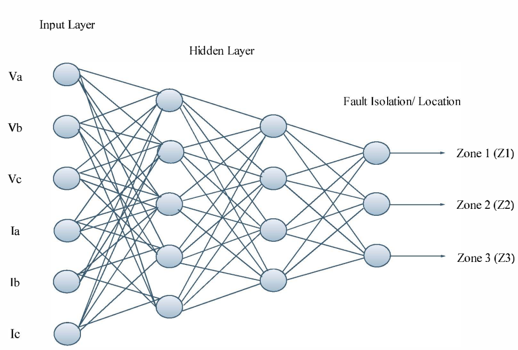

Fig. 10. Back Propagation Neural network chosen for fault isolation.

V. CONCLUSION

This thesis has investigated the use of back-propagation (BP) neural network architecture as an alternative method for fault detection, classification and isolation in a transmission line system. It uses RMS values of phase voltage and phase current as inputs. Simulation models of the transmission line system are constructed and the generated information is then channeled using MATLAB software (Version 7) and accompanying Power System Block Set (Version 2.1). Neuroshell 2 software is also used to provide back-propagation neural networks. Three common faults were discussed; single phase to ground faults, double phase faults and double phase to ground faults. Due to the flexibility of the neural networks which accept any real values (highly correlated or independent) as an input, resistant to errors in the training data and fast evaluation. The results obtained demonstrate that the performance of the back-propagation (BP) neural network architecture was highly satisfactory.

Neural networks, in general, provide a reliable and an attractive alternative approach for the development of a protection relaying system for the power transmission systems.

VI. REFERENCE

[1] Laurene V. Fausett, Fundamentals of Neural Networks: Architectures, Algorithms, and Applications, Prentice Hall, 1993.

[2] Nasser D. Tleis, Power Systems Modeling and Fault Analysis Theory and Practice, Elsevier Ltd, 2008.

[3] Hagan MT, Demuth HB, Beale MH, '*Neural network design*, PWS Publishing, 1996.

[4] Kevin Gurney, an Introduction to Neural Networks, UCL Press, 1997.

[5] Arthur R. Bergen and Vijay Vittal, *Power Systems Analysis* - 2nd Edition, Prentice Hall, 2000.

[6] C. R. Bayliss, B. J. Hardy, *Transmission and Distribution Electrical Engineering* – Third Edition, Newnes, 2007.

[7] R. Kamyab Moghadas and S. Gholizadeh "A New Wavelet Back Propagation Neural Networks for Structural Dynamic Analysis" *IAENG, Engineering Letters*, February 2008.

[8] O A A Elmubark, "Fault Detection, Classification and Location in Power Transmission Line System Using Artificial Neural Network," MSc. dissertation, Dept. Elec. Eng., Sudan Univ. of Sci. & Tech. Khartoum, March 2011

VII. BIOGRAPHY

Eisa Bashier M Tayeb; was born in Wadbunda in the northern Kurdofan State, Sudan; on Jan 1964. He graduated from the Khartoum Polytechnic, and studied MSc in Instrumentation & Control at Aligarh Muslim University; India. His PhD in Electronics Instrumentation was also from AMU-India. His total employment experience is 20 years at SUST.

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