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Faults Detection in Power Systems Using Artificial Neural Network

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Abstract:- Electrical power systems suffer from unexpected failures due to various random causes. Unpredicted faults that occur in power systems are required to prevent from propagation to other area in the protective system. The functions of the protective systems are to detect, then classify and finally determine the location of the faulty line of voltage and/or current line magnitudes. Then at last, for isolation of the faulty line the protective relay have to send a signal to the circuit breaker. The ability to learn, generalize and parallel processing, pattern classifiers is powerful applications of NN used as an intelligent means for detection. This paper presents neural network NN architecture for fault detection in a transmission line power system. It aims to implement complete scheme for distance protection that subdivided into different neural networks zones. Single phase to ground, double phase and double phase to ground faults are considered. As a result a protection relaying system for the power transmission line systems can be done using the NNBP architecture.

I.   INTRODUCTION

The electrical system faults are the greatest threat to the continuity of electricity supply. 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 and 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].

Electrical power systems control centers contain a large number of alarms received as a result of different types of faults. To protect these systems, the faults must be detected and isolated accurately. Majority of short-circuit faults tend to occur on overhead lines [2]. The operators in the control centers have to deal with a large amount of data to get the required information about the faults.

Through the years artificial neural networks [3, 4]*,* have been invented with both biological ideas and control applications in mind, and the theories of the brain and nervous system have used ideas from control system theory [5].

The neural network represents a network with a finite number of layers consisting of solitary elements that are similar to neurons with different types of connection between layers. The number of neurons in the layers is selected to be sufficient for the provision of the required problem solving quality. The number of layers is desired to be minimal in order to decrease the problem solving time [1, 6].

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. 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 [7 - 9]. NN used for overhead transmission lines [10, 11], as well as in power distribution systems [12, 13].

This paper presents a method for detection and identification of the fault type and its zone in the line. Backpropagation neural network approach is studied and implemented. Voltages and currents signals of the line are observed to perform these three tasks. The detailed coefficients of all phase current signals that are collected only at the sending end of a transmission line are selected as parameters for fault classification [14].

The transmission line models are constructed and simulated to generate information which 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 LINE MODEL

Pi model network for AC overhead transmission lines is used to model 110 kV transmission line system connects two cities (namely; EL FAU and GEDAREF). The line length is 145 Km, this line is used to develop and implement the proposed architectures and algorithms for this problem. Fig. 1 shows a single-line diagram of the system used to train and test the neural networks. The system consists of two Substations one in each city at the beginning and the end of the transmission line [15].
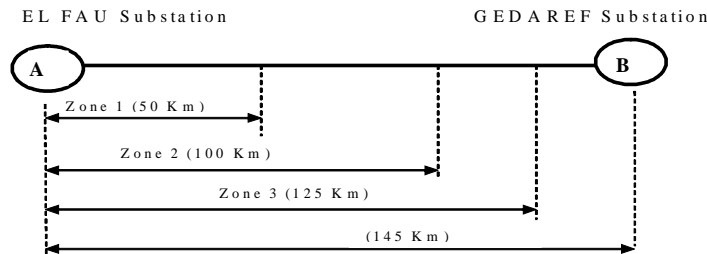

Fig. 1 ELFAU GEDAREF Transmission Line

In Fig. 1 the three-phase voltages and currents, V = [Va Vb Vc]^T and I = [Ia Ib Ic]^T are measured at substation A. The three simulations categories (phase to ground faults; phase to phase faults and double-phase to ground faults are presented.

III.   CONVENTIONAL BACKPROPAGATION ALGORITHM

Recently, multilayer neural networks have been applied successfully to solve lots of difficult and diverse problems through employing various supervised learning procedures among which the error Backpropagation (BP) learning algorithm appears to be the most popular. This algorithm is an iterative gradient based algorithm proposed to minimize an error between the actual output vector of the network and the desired output vector. The term back propagation refers to the manner in which the gradient is computed for nonlinear multilayer neural networks [16]. The output of all hidden layers and the output layer are obtained by propagating the training patterns through the network. Let us define the matrix:

$$O^\ell = A^\ell W^\ell \qquad \text{.............. (1)}$$

The entries of $A^{\ell+1}$ for all layers ($\ell = 1,2..., L-1$) are evaluated as:

$$a_{p,j}^{\ell+1} = f(O_{p,j}^\ell) \qquad \text{............ (2)}$$

Where; $p = 1,....,P$ and $j = 1,2,......n_{\ell+1}$

An algorithm is required to adjust the weights so that the network learns how to map the input patterns to the output patterns. The most widely used algorithm for training feedforward neural networks is the BP algorithm. Learning is achieved by adjusting the weights such that the network output, A^L is as close as possible or equal to the target, T^L. The error is given as:

$$E = \frac{1}{2P}\sum_{p=1}^{P}\sum_{j=1}^{n_L}(t_{p,j} - a_{p,j}^L)^2 \qquad \text{......... (3)}$$

So, we need to minimize the error E, with respect to the weight changes $W_{i,j}$. We follow the delta rule to incorporate the learning rate η, along with the gradient descent algorithm techniques to

define the weight change. The changes of weights are proportional to the error gradient [17]. Mathematically,

$$\Delta W_{ij}^{\ell} = -\eta . \frac{\partial E}{\partial W_{ij}}; \qquad 0 < \eta \le 1 \quad \ldots\ldots\ldots (4)$$

If the gradient $\frac{\partial E}{\partial W_{i,j}}$ is positive then the weight change should be negative and vice versa. Hence, a

minus sign is added at the right hand side of (4).

The weight changes $\Delta W_{i,j}^{L-1}$ for the weights connecting to the final layer are obtained by:

$$\Delta W_{i,j}^{L-1} = -\frac{\eta}{2P} \sum_{p=1}^{P} \sum_{j=1}^{n_L} \frac{\partial}{\partial W_{i,j}^{L-1}} (t_{p.j} - a_{p,j}^L)^2 \qquad \ldots (5)$$

Notice that for a given *j*, only $a_{p,j}^L$ has a relation with $W_{i,j}^{L-1}$, we get:

$$\Delta W_{i,j}^{L-1} = \frac{\eta}{P} \sum_{p=1}^{P} (t_{p.j} - a_{p,j}^L) \frac{\partial a_{p,j}^L}{\partial W_{i,j}^{L-1}} \qquad \ldots\ldots (6)$$

The partial derivative $\frac{\partial a_{p,j}^L}{\partial W_{i,j}^{L-1}}$ can be evaluated using the chain rule. From equations (5) and (6)

$$\Delta W_{i,j}^{L-1} = \frac{\eta}{P} \sum_{p=1}^{P} (t_{p.j} - a_{p,j}^L) f'(o_{p,j}^{L-1}) a_{p,i}^{L-1} = \frac{\eta}{P} \sum_{p=1}^{P} \delta_{p,j}^{L-1} a_{p,i}^{L-1} \qquad \ldots\ldots. (7)$$

Where; $\delta_{p,j}^{L-1} = (t_{p.j} - a_{p,j}^L) f'(o_{p,j}^{L-1})$ and $f'(o_{p,j}^{L-1}) = \frac{\partial a_{p,j}^L}{\partial o_{i,j}^{L-1}}$

By analogy the weights change for other lower layers of weights are:

$$\Delta W_{i,j}^{\ell} = \frac{\eta}{P} \sum_{p=1}^{P} \delta_{p,j}^{\ell} a_{p,i}^{\ell} \qquad\qquad \ell = 1,\ldots,L-1$$

and

$$\delta_{p,j}^{\ell} = \sum_{k=1}^{n_{\ell+1}} \left[\delta_{p,k}^{\ell+1} w_{j,k}^{\ell+1} \right] f'(o_{p,j}^{\ell}) \quad \ell = 1,\ldots,L-1$$

The learning procedure therefore consists of the network starting with a random set of weight values, choosing one of the training patterns and evaluating the output(s) using that pattern as input in a feedforward manner. Using the BP procedure, all the weight changes for that pattern are evaluated. This procedure is repeated for all the patterns in the training set so that for all the weights ($\Delta w_{i,j}$) are obtained. Then corrections to the weights are made.

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

IV.   DESIGN OF ANN FOR TRANSMISSION LINE

Artificial neural network (ANN) 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). In the process of learning the neural network presented with pairs of input and output data then teached how to produce the output when the corresponding input is presented. Through iterative training procedure the network's weights are adjusted by the error signal in a way that the network output tries to follow the desired output as close as possible. The learning procedure continues until the error signal is close to zero or below a predefined value. The sum of errors over all the training samples can be considered as a kind of network performance measure, which is a function of free parameters of the

system. Such function can be visualized a multidimensional error surface where network free parameters serves as coordinates. During the course of learning the system gradually moves to a minimum point along an error surface. The error surface is determined by the network architecture and the cost function [17, 4].

Data generated from the transmission line system are collected, trained and tested. The detection of a fault situation in the system is the first step. Following that is the investigation of the fault class and finally location of the faulty zone to be isolated.

4.1 NEURAL NETWORK DESIGN FOR FAULT DETECTION

Extensive simulations of the output error at the network output have been made using data of table (1). Fig 2 shows three layers BPNN used for fault detection. NN were tried with different neurons in each layer. Fig 3 shows the output errors obtained for NNs with 6-2-1, 6-3-1 and 6-4-1 neurons in each layer. As a result of these errors; it was decided to select the network which has 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 [15].

TABLE 1 PER UNIT VOLTAGE AND CURRENT TRAINING SET

Case NO.	Input Vector (P.U)						Fault Type
	Va	Vb	Vc	Ia	Ib	Ic	
1	.997	.9991	.9985	.9978	.9988	.9984	No fault
2	0.334	1.194	1.172	3.335	0.981	0.979	A to Grd
3	1.172	0.334	1.194	0.981	3.335	0.979	B to Grd
4	1.194	1.172	0.334	0.981	0.979	3.335	C to Grd
5	0.471	0.650	.986	5.379	5.379	0.983	A to B
6	0.986	0.471	0.650	0.984	5.379	5.379	B to C
7	0.471	.986	0.650	5.379	0.984	5.379	A to C
8	0.205	0.205	1.188	7.187	7.855	0.985	A to B to Grd
9	1.188	0.205	0.205	0.985	7.187	7.855	B to C to Grd
10	0.205	1.188	0.205	7.187	0.985	7.855	A to C to Grd

The selected network is then tested with a new set of data which was not used before created to analyze its performance. The performance of network for input/output is shown in fig.4.
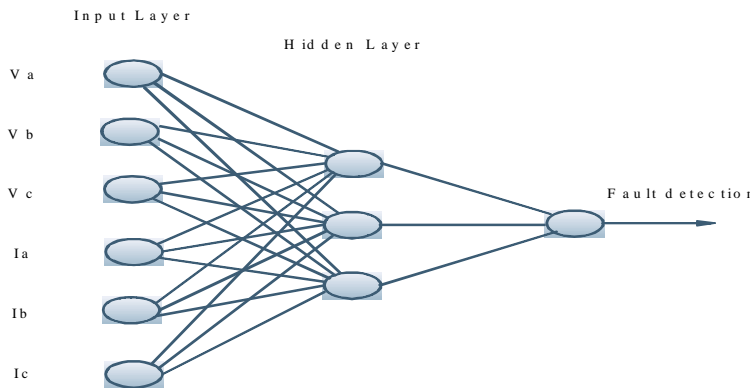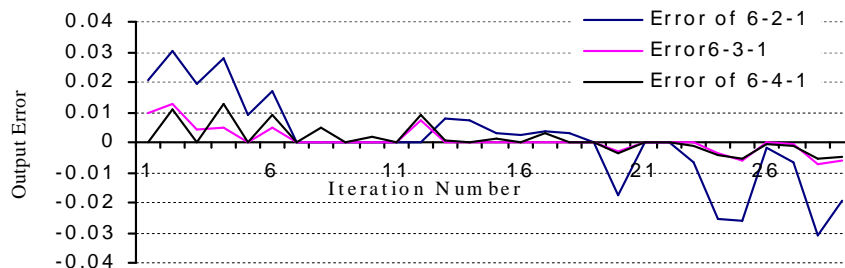

Fig.2. BPNN for Fault Detection

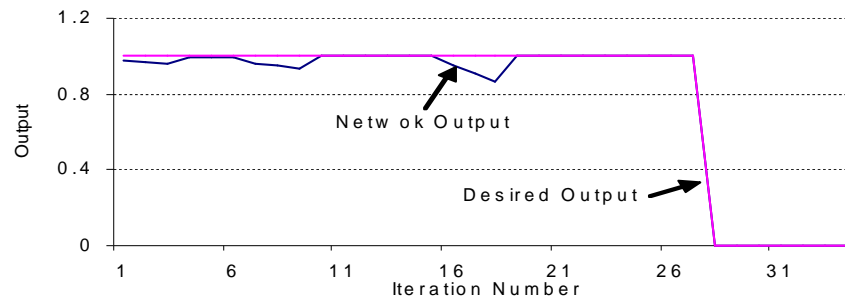Fig.3. Output error for the BPNN with 6-2-1; 6-3-1and 6-4-1 neurons

Fig.4. Testing Samples Network output versus desired output for the BPNN 6-3-1

4.2 NEURAL NETWORK DESIGN FOR FAULT CLASSIFICATION

There are three phases (A, B, C) and neutral or ground G or Grd. their combinations are subjected to faults. The data required to differentiate between these types of faults are the three phase voltages and currents. This data generates four output statuses associated with the four fault categories. The outputs contain variables whose values are given as either 0 or 1 corresponding to the existence of that class of fault.

The proposed NN should classify if the specific phases involved in the fault scenario or not. The combinations generate nine different categories of faults as illustrated in Table 2. This designed NN should be able to distinguish between them.

TABLE 2 BPNN CLASSIFICATION NETWORK TRUTH TABLE

Fault Situation	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-A	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 three layers networks were extensively simulated and studied. The input and output layers has fixed six (three phase voltages and currents) and four neurons, respectively. The hidden layer is tried with different neurons numbers. The most suitable network size for the classification task was found to be hidden layer with five hidden neurons as shown in Fig.5. The activation function at input layer is linear (-1, 1) function while at hidden layer and output layer is logistic function. Error plot of the testing set is shown in fig.6. The selected network was able to recognize correctly the type of the fault category.
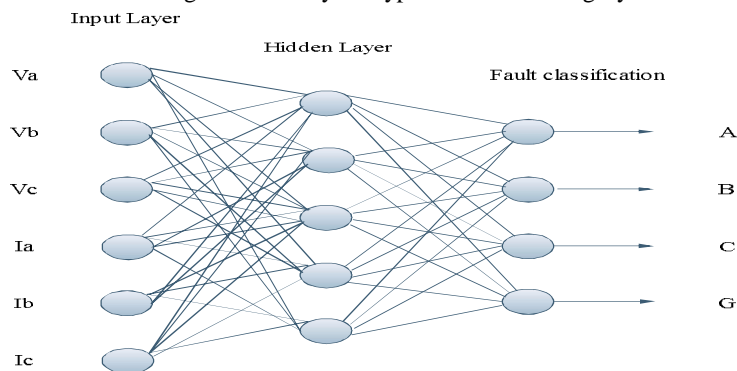

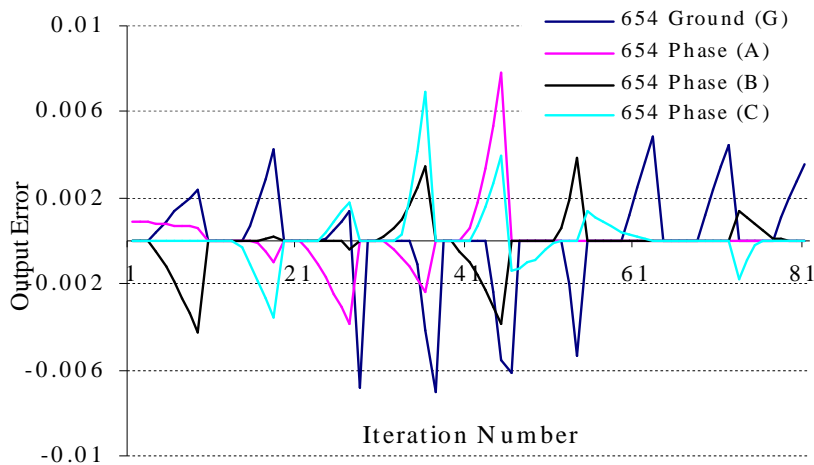Fig.5   Back Propagation NN for Fault Classification

Fig.6   Testing samples output error BPNN 6-5-4

4.3 NEURAL NETWORK DESIGN FOR FAULT LOCATION

Detection of fault location has to be done for the purpose of isolating the faulty section of the system. The network is expected to identify the location of the fault by classifying the identified fault into one of the three fault zones, namely Zone 1, 2 and 3. The proposed neural networks here should isolate the specific zone involved in the fault network as shown in the network training Table 3.

TABLE 3 ISOLATION NN TRAINING SET

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 BPNN with different structures were studied and analyzed. This time network which has two hidden layers is tried. The training includes some of the selected networks structures (6-5-5-3, 6-6-6-3, 6-7-6-3 and 6-5-4-3). It is found that 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. Again 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 Fig.7.
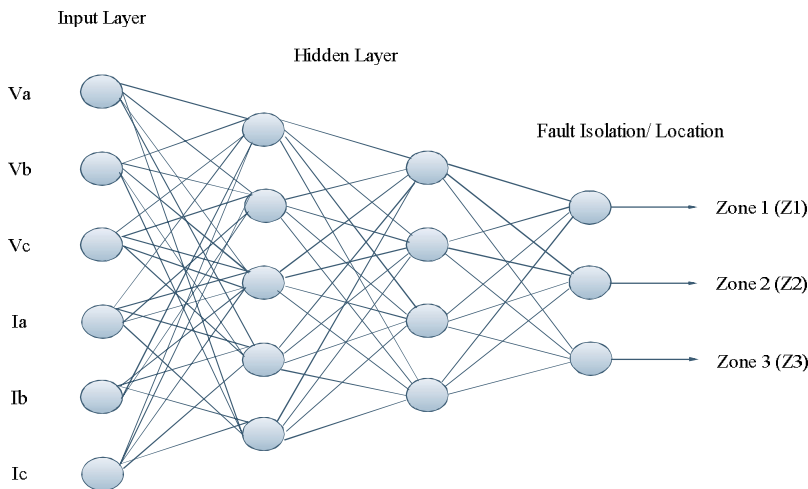

Fig.7 Back Propagation NN chosen for fault isolation

A new set of test data samples was created to analyze the performance of the proposed network. A fault cases for each location of fault were utilized in the test set. Output error plot of the testing set is shown in fig 8. The selected network from the previous section was able to recognize correctly the location of the fault.
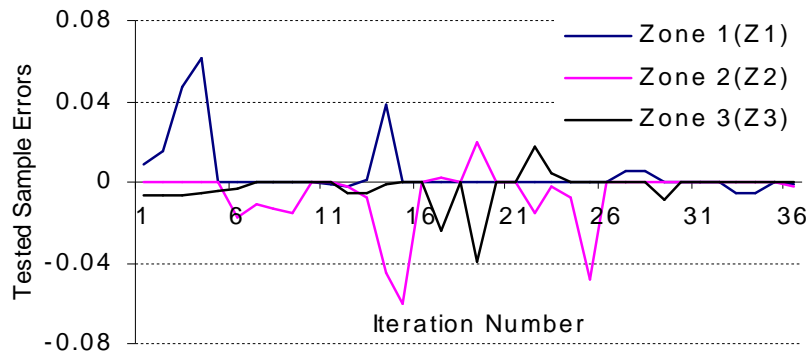

Fig. 8   Testing samples output error for the BPNN 6-5-4-3

V.   CONCLUSION

This paper fault detection, classification and location in a transmission line system have been investigated using neural network backpropagation (BP) algorithm. MATLAB-7, Power System Block Set-2.1and Neuroshell-2 software were used for simulation of the transmission line models. Data generated is used for single phase to ground faults, double phase faults and double phase to ground faults. The multi-layer neural networks were trained with the generated data. When real values are then used as an input to trained NN; fast evaluation of errors obtained. The results obtained for transmission line fault detection, classification and locations finding all were highly satisfactory using BPNN architecture.

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