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Fault Detection and Diagnosis Based on Artificial Neural Network

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Abstract— This paper presents the detection and classification of different types of faults occurred in the transmission power system. The artificial neural network detects, classifies and locates any sudden fault in the power system in a fast and accurate algorithm. The back propagation is used as a learning algorithm because it can execute and process a huge data. Three cases: single fault, multiple faults and sequential faults are investigated with artificial neural network. IEEE 14-Bus test system is used to verify the proposed method..

Index Terms— Artificial Neural Network, fault detection, fault location, transmission line, ANN detector, Artificial Intelligent application, Transmission system protection.

1 INTRODUCTION

The most important problems facing the electrical engineer are the faults in the electrical power systems that occur in the transmission line system. In addition, the faults reduce the ability to fill the requisite of the necessary electrical power system [1]. Most faults on transmission lines are caused by a temporary occurrence such as lightning, conductor swing, trees, etc. The main types of fault are symmetrical and unsymmetrical.

The need has become urgent to use the protection systems with a high efficiency in detecting the faults rapidity and accurately. Furthermore, one of the occurrence of an exceptional event and power outages leads to a short circuit condition [2]. A heavy short circuit current that flows through the equipment causes a damage and interruption of service. Practically, every equipment and apparatus ratings in the power system are selected by the considerations of the short circuit current.

The faults on power system transmission are supposed to be first detected and then classified according to the fault types. The faults should be cleared as soon as possible. Therefore, an efficient, reliable, fast and secure fault detection should be provided.

The fault analysis of the transmission lines was discussed by many researchers. Three outstanding subjects are to be considered, detection, diagnosis and location of the faults in order to protect the power system and enhance its performance. These researches utilized the various types and methods for the fault analysis. The coming paragraphs review briefly some of the researches that utilized different approaches.

W.Qi, G.W.Swift, and et.al. (2006) [3] proposed a distance protection based on the artificial neural networks (ANNs). The data was taken from the test system simulation under two conditions of operation, which are normal load and fault, and used for training these neural networks. The fault detection of more selective arcing was the important part in this research and its concentration on creating it, especially for transmission lines of radial types where the zero-sequence impedance can be satisfied by the arc resistance. The data was provided by a non-linear model of the arcing resistance and the characteristic of the new operation was devised.

Marcin Mrugalski and et.al, (2006) [4] used an artificial neural network in the method of the identification to get a robust detection of the fault in the transmission lines. This research considered a problem of the uncertainty estimation for the neural network with multi-layer perceptron. The solving of the fault detection problem of the DAMADICS (Development of Applications and Methods for Actuator Diagnosis in Industrial Control System) benchmark was presented.

H. Abniki, and et.al, (2012) [5] proposed a method of fault detection based on an impedance technique for overhead lines of transmission system. This method, which was fast and reliable, was desirable and necessary. ANN (Artificial Neural Network) was used for presenting this method. In this regard, the algorithm of feed-forward back-propagation (FFBP) was used for training the ANN by using the values of the zero-sequence impedance. EMTDC software was used for simulation and the results were accurate and appropriate to the proposed conditions of the technique.

A.P.A. da Silva, and et.al, (2012) [6] proposed the relationship between the variables of electricity, which are voltages and currents, and the transmission lines fault locations by using the neural network of complex-domain. These networks prevented the amplitude and phase from decoupling during the representation of the electrical variables.

Eisa Bashier M Tayeb, (2013) [7] modified an architecture of the neural network to detect the fault that occurs in the transmission line. The goal of this paper was to prevent the fault from propagation to other areas in the system by the implementation of a robust system for the distance protection depending on several neural networks, each one for specific zone.

Z. He, and et.al, (2014) [8] presented a new approach for classification of the fault that occurs in the transmission lines of super high voltage by using a neural network of a rough membership (RMNN) classifier. Ten of these classifiers were used to decide the type of the transmission line fault. Furthermore, the neurons of the input layer were the rough neurons in order to reduce the time of the training for the neural network. The output and the hidden layers used the fuzzy neurons in each RMNN.

J. Upendar, C.P. Gupta and G.K. Singh, (2011) [9] studied the protection system of the transmission lines and proposed a statistical algorithm to classify the types of faults. The classification and regression tree (CART) method and the wavelet method, used to transform currents flowing at the sending terminals, were used to describe the proposed algorithm. A hidden information was constructed from the current signals by the wavelet transform and then it was used in the CART method as input values to get out the clearly information about the fault type.

R. Malkar, V. Magdum and S. Kumar Gunda, (2012) [10] proposed a method to analyze the disturbance in power system based on the wavelet transform for solving the fault problems that occur in the transmission lines with biorthogonal and haar wavelet. In the proposed research, the faulted transmission line was detected by the wavelet transform. The selection of the suitable wavelet for the detection of the faulted-phase application depended on the discrete approximation coefficient of the dyadic wavelet transform.

F. Martín, and et.al, (2008) [11] proposed a method for protection of double circuit transmission system depending on the digital relays. The proposed method consisted of primary module of processing depending on the transformation of the time and frequency aided by ANN for fault detection and classification of its type. The pre-processor used in this research was the wavelet transform daubechies 6.

Anamika Yadav and et.al, (2014) [12] provided an artificial neural network approach for fault detection, fault classification, fault location, fault phase selection, and fault direction discrimination. Artificial neural networks can be trained with offline data. The protective relay uses current and voltage signals to detect.

Christian Flytkaer Jensen (2014) [13] presented an online fault location methods for cross bonded cables in underground transmission systems. He identified the advantages and weaknesses of the exciting offline methods.

It can be observed that there are many researches based on artificial intelligent approaches such as neural network, fuzzy logic, or genetic algorithm that are considered for the fault detection, fault classification, and fault location [3]-[10]. Some authors implemented an adaptive protection scheme using an artificial neural network. Numerous researchers used the support vector machine and wavelet network for fault detection [11]-[13]. However, some authors uses a hybrid system comprising a wavelet network for the fault detection and artificial intelligent method for the classification and location of the fault in the power system. An accurate and fast method will be the most important matter to be taken into consideration.

Artificial neural network is proposed in this paper because it is a reliable and effective approach for the detection of the fault in the transmission power system in order to increase the performance of the practical application. Three cases have been considered to verify the operation of the proposed algorithm

2 ARTIFICIAL NEURAL NETWORK (ANN)

Concerning the normal and abnormal conditions of operation of the power system, the faults to be discussed in succeeding sections involving the impedance between lines and from one line or two lines to ground [2].

Nowadays, a lot of books and scientific research deal with artificial neurons and their potential to solve problems relating various disciplines and fields. The mechanism of the neural network design will be structured. The designed model will be implemented on the IEEE 14 bus standard network trained in order to be able to discover fault types and location.

2.1 The Model of individual Neuron

Artificial neurons are considered as the basic unit of the creation of the artificial neural network. They perform the function of the biological neurons in human brains but in mathematical form, and this is what gives them the ability to treat the various problems in different fields [14]. The Model of Neuron is shown in Figure 1.

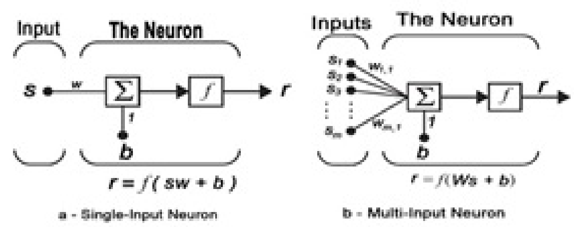

Fig. 1. The model of neuron.

Neurons consist of combines as illustrated in the following parts:

1. Input Data (Single or Multiple) (s)

It is the scalar data sent to neuron as scalar vector. It is multiplied by the weights to form (ws), where (w) is the weight. At first, this data comes from the system as a set of vectors to train the neural network and the synaptic weights are obtained at off-line processing. After that, individual vectors come at on-line processing to detect what it is trained on [14].

2. Synaptic Weight (w)

It is the strength to each connect between the neuron input and the neuron itself. It is the scalar value between (0 – 1), multiplied by the corresponding input data.

3. Bias (b)

It is the offset of the neuron, which is also an input data but whose weight is one. It is clear that the total input to each neuron is equal to the summing of (ws+b).

4. Activation Function (f)

It is also called, transfer function, which defines the output of each neuron. An activation function is chosen from different functions to satisfy some boundaries of the problem that the neuron is trying to solve.

The hard limit function is shown in Figure 2 (a) where if the argument of the activation function is equal/more than 0, it gives 1 on the output, and it gives 0 if the argument is less than 0.

Figure 2 (b) shows the characteristic of the input and output for the single input neuron, where it shows the effect of the bias by deviate the function to the left.

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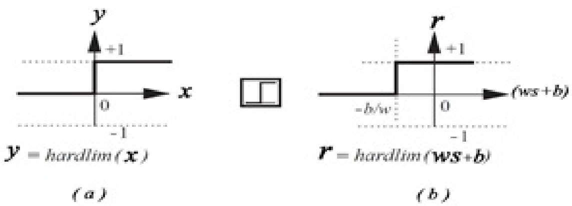

Fig. 2. The model of neuron.

The log-sigmoid activation function is the second commonly used transfer function, where its arguments have a wide range from minus to plus infinity and gives the output in the following expression:

$$y = \frac{1}{1+e^{-x}} \quad (1)$$

Because of the wide range of arguments of sigmoid function, it is used as activation function in this thesis. Also it is non-linear, and can get its derivative, so it makes the neural network have the ability to simulate the non-linear mapping characteristic.

3 Architecture of Neural Network

Generally single neuron, with/without multiple inputs, cannot solve problems sufficiently. The problem might need six or more neurons, connected in parallel with each other, in what is called "Layer". The concept of layer will be describe in the next section [14].

3.1 A Layer of Neurons

Figure 3 shows the single-layer of n neurons (as an output neurons), where, each individual input from m inputs is connected to each neurons. Thus, the weight matrix will have (m*n) size

$$\mathbf{W} = \begin{bmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,N} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,N} \\ \vdots & \vdots & & \vdots \\ w_{M,1} & w_{M,2} & \cdots & w_{M,N} \end{bmatrix}$$

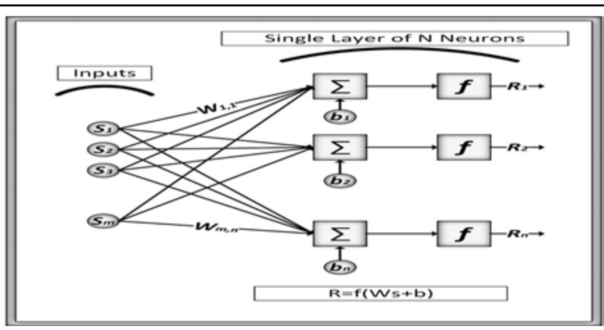

Fig. 3. Single layer network of N neurons.

It should be noted that the activation function of the neurons at the same layer should not be the same; therefore the activation functions are different in the layer.

The weight matrix, that the input elements enter the network through it as given:

The general output function of the single layer neural network is given in the following expression:

$$R_n = f\left(\sum_{i=1}^{m} s_i w_{in} + b_n\right) \quad (2)$$

As shown previously, the columns of the matrix W refer to the destination neurons of the neural network, while the rows of the matrix W refer to the source of the inputs.

Fortunately, the m-Input, n-Neuron, single layer neural network also can be represented in the abbreviated notation as shown in Figure 4.

The symbols below each variable tell that S is an n-element vector, W is a matrix of m*n size, and b and R are n-element vectors [14].

Each element of the input vector is connected to each neuron input through weight matrix W. It is clear that the number of inputs to a layer is to be different from the neurons.

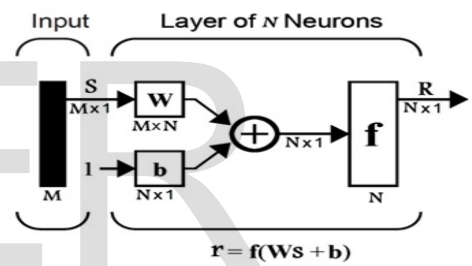

Fig. 4. Single layer network of N neurons.

3.2 Multi-Layers of Neurons

It is the network that has multi stages of processing for input data. The input of the first stage is the network input data and then, the input of the next stage will be equal to the output of the previous stage, and so in the other stages until reach to the final output of the neural network.

Figure 5 shows an artificial neural network of three layers of neurons. The superscripts are used to identify the number of the layer.

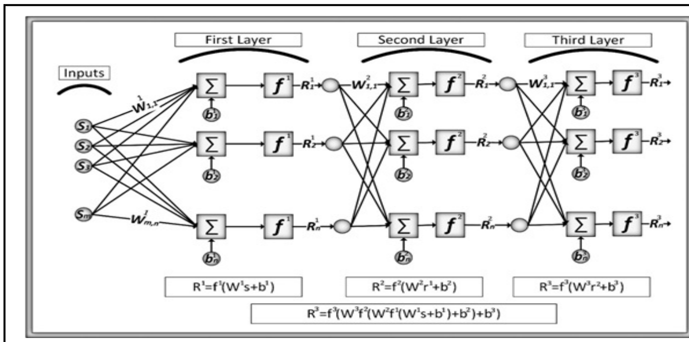

Fig. 5. Multi-layer network

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The third layer is called the output layer because it gives the final output, but the two other remaining layers are called the hidden layers.

4 THE SOFTWARE MECHANISM

The input data will flow in multiple stages of processing and treatment until reaching the desired results. Thus, the software consists of different types of operation. This software was implemented on two test systems of IEEE standard, 14-bus system. The flowchart for the programming mechanism is shown in Figure 6.

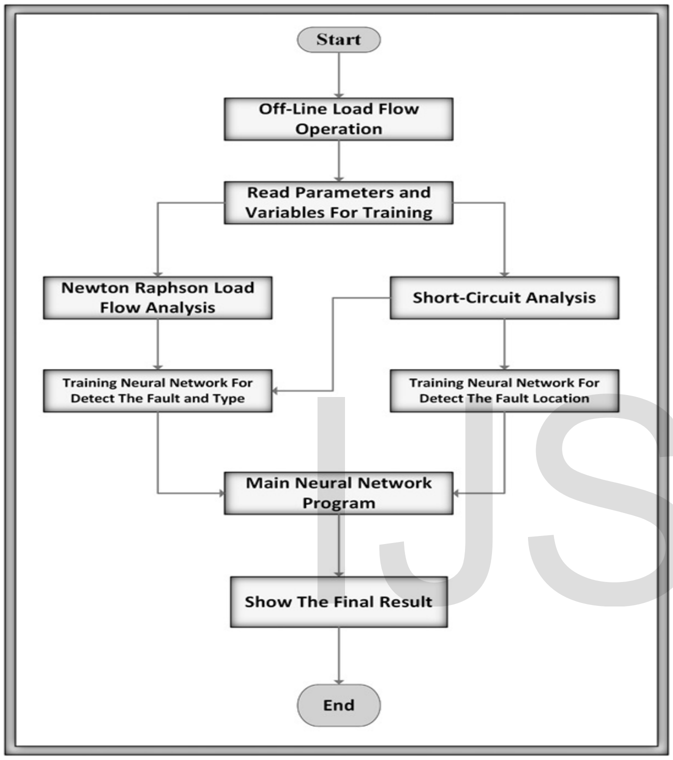


Fig. 6. The fault analysis flowchart using ANN

5 SIMULATION RESULTS AND DISCUSSION

The test system consists of 14-bus and 17-line and the neural network program will be applied to know its ability on detect the faulted line. The single line diagram of this system is shown in Figure 7. Three cases have been regarded, signle fault, multiple, and sequential fault. The line data and bus data are given in appendix

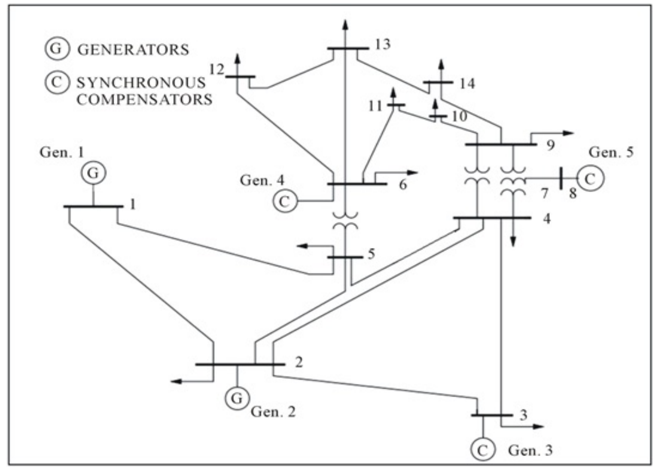


Fig. 7. : Single line diagram for 14-bus IEEE system.

5.1 Single fault test

Assuming double-line-to-ground fault occurs in the system mentioned earlier and the faulted point will be lying on the line between the two buses, bus-1 and bus-5, which is the red line in Figure 8. Figure 9 shows the fault analysis simulation result for double line to ground.

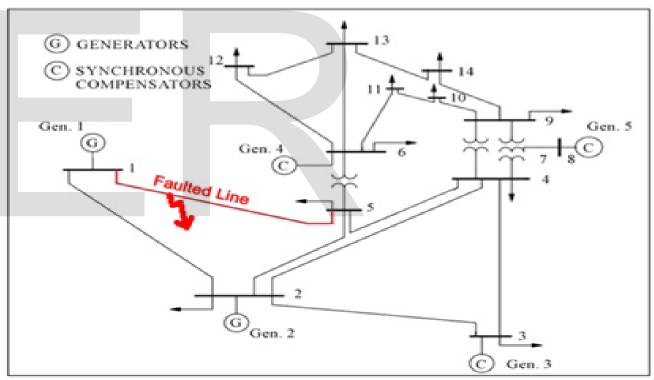
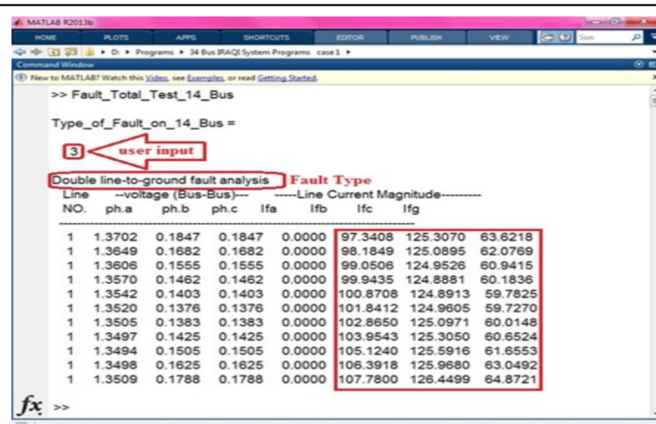


Fig. 8. : The faulted line in red line



Line NO.	--voltage (Bus-Bus)--- ph.a	ph.b	ph.c	------Line Current Magnitude--------- Ifa	Ifb	Ifc	Ifg
1	1.3702	0.1847	0.1847	0.0000	97.3408	125.3070	63.6218
1	1.3649	0.1682	0.1682	0.0000	98.1849	125.0895	62.0769
1	1.3606	0.1555	0.1555	0.0000	99.0506	124.9526	60.9415
1	1.3570	0.1462	0.1462	0.0000	99.9435	124.8881	60.1836
1	1.3542	0.1403	0.1403	0.0000	100.8708	124.8913	59.7825
1	1.3520	0.1376	0.1376	0.0000	101.8412	124.9605	59.7270
1	1.3505	0.1383	0.1383	0.0000	102.8650	125.0971	60.0148
1	1.3497	0.1425	0.1425	0.0000	103.9543	125.3050	60.6524
1	1.3494	0.1505	0.1505	0.0000	105.1240	125.5916	61.6553
1	1.3498	0.1625	0.1625	0.0000	106.3918	125.9680	63.0492
1	1.3509	0.1788	0.1788	0.0000	107.7800	126.4499	64.8721

Fig. 9. : The results of double-line-to-ground fault analysis for 14-bus

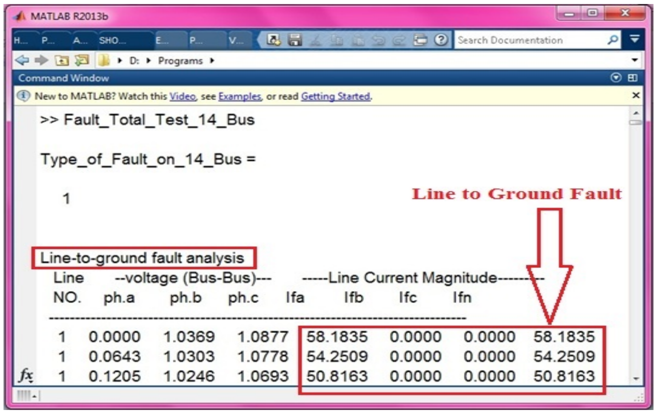


Fig. 13. The results of line-to-ground fault analysis for 14-bus

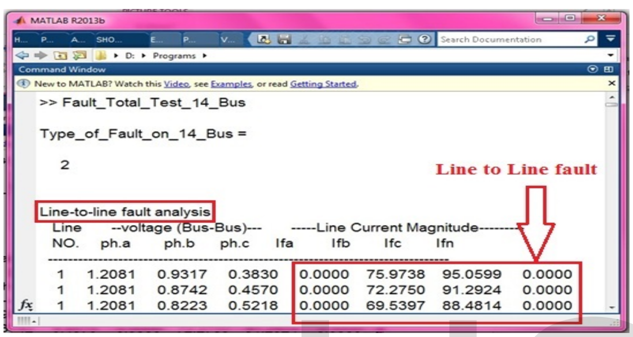


Fig. 14. The results of line-to-line fault analysis for 14-bus

Fig. 10. : Learning process and performance curve of double line to ground neural network for 14-bus test system

Now, the neural network is ready to test the double line to ground fault on any line of the system and detect it. But, to make the neural network have the ability for detecting all other types of fault, another learning process should be made up, which will be made in the second case. Figure 11 shows the result of testing the fault that occurs on line 1.

Figure 11 has the required information about the type of the occurring fault, the number of the faulted line and the distance of the faulted point far away from the sending end, which is at the end of line-1

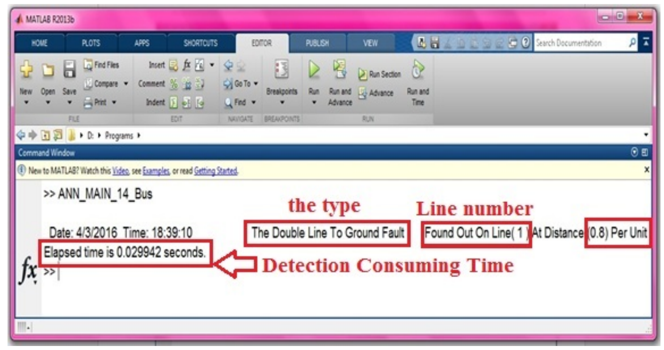


Fig. 11. : The detection result for a single case of fault for 14-bus

5.2 Study Case II: Multiple Fault Test

In this case, multi types of faults will occur at the same instant, with the purpose of the neural networks to be ready to detect all types of fault at the same time and give a robust details about each type.

Therefore, the neural networks should learn all types of fault and also the normal operation of the system to be able to distinguish whether the system is faulted or at a normal operation.

The first data sets needed for learning are obtained from the short circuit analysis programs, while the second data set is obtained from the offline Newton-Raphson load flow analysis.

The results of these programs are shown in Figures 12, 13 and 14.

Note: the double line to ground analysis is similar to that in the first case because the system does not change, so that the computation will be only for the other fault types.

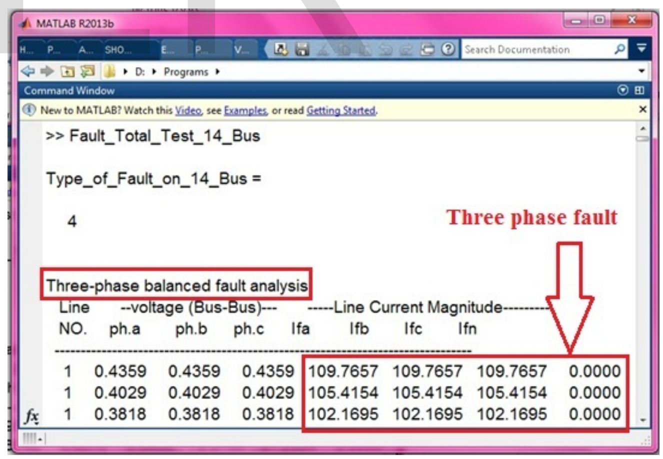


Fig. 12. The results of symmetrical three phase fault analysis for 14-bus

Besides, the artificial neural networks will be learned by us-

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ing these three data sets. The learning process is shown in Figure 15.

The neural networks are promptly ready to test the multiple types of the fault on any line of the system and detect it. Figure 16 shows the results for different situations of test on different lines.

5.3 Study Case III: Sequential Fault Test

Assuming that the first fault that occurred in the first case, where the faulted point was lied on the line between the bus-1 and bus-5 and then, the faulted line was removed, the new system will consist of 16-lines instead of the original system which was 17-lines. In brief, this case studying the possibility of two or more events that can occur simultaneously.

For the reasons mentioned above, a new computation will be presented to the 16-line system by applying the load flow Newton Raphson analysis and short circuit analysis programs in order to get out the essential sets of data that will be used for learning the neural network and making them ready to detect a new situation. These computation results are shown in Figure 17.

6 Detection and Learning Consuming times

The table (1) shows the consuming times for detection and learning algorithm time for double line to ground fault. These consuming times are affected by the case conditions for each system. These consuming times depend on the PC specification used in implementing the program.

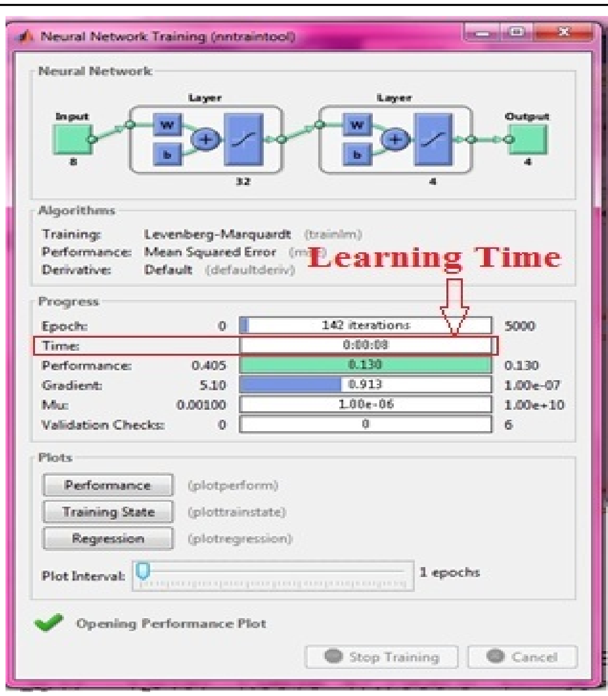

Fig. 15. Learning process and performance curve of symmetrical three phase neural network for 14-bus

7 Conclusion

The study included fault detection, classification and fault locating in the transmission power system. Since the fault detection in a transmission line is not always easy to do because it requires analyzing the data to be transmitted to the control center. The method is based on artificial neural network. The possibility of one or more events that occurred were studied and for different type of faults. The simulation results showed that not only can a fault be precisely identified and detected but also the fault can be located correctly.

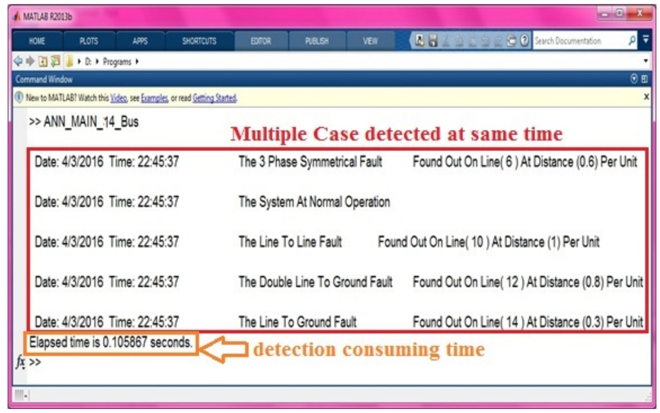

Fig. 16. The detection results for multiple case of fault for 14-bus

The system can be enhanced when the real time load flow program is used. Supervisory Control and Data Acquisition (SCADA) is capable of monitoring or controlling the system and can check the status of each equipment (as circuit breakers) and data (as voltage or current).

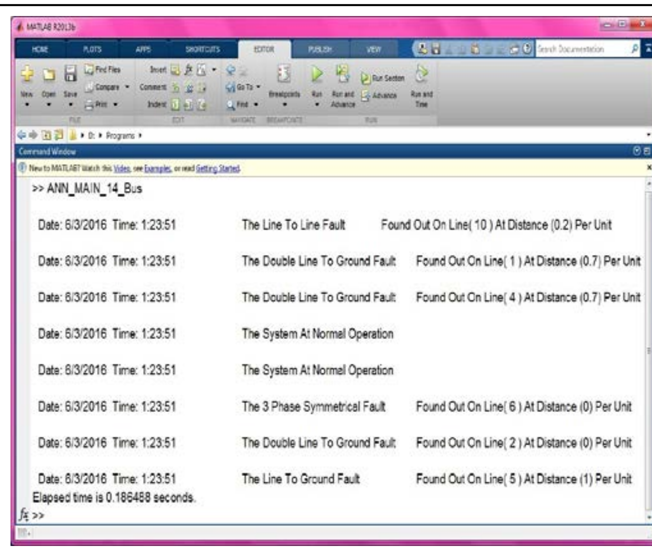

Fig. 17. The detection results for sequential case of fault for 14-bus

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TABLE 1
LEARNING AND DETECTION CONSUMING TIMES OF ONLY DOUBLE LINE TO GROUND FAULT FOR ALL THE THREE SYSTEMS

System	learning consuming time xx(min):yy(sec)			detection consuming time (sec)		
	single case	multiple case	sequential case	single case	multiple case	sequential case
14-bus test system	00:30	00:30	00:28	0.029942	0.105867	0.186488

Appendices

Test System Data

I. 14-Bus IEEE system

Bus	Type	|V| p.u	Angle degree	Pl p.u	Ql p.u	Pg p.u	Qg p.u	Qmin p.u	Qmax p.u	Q inject
1	1	1.06	0	0	0	0	0	0	0	0
2	2	1.045	0	21.7	12.7	40	42.4	-40	50	0
3	2	1.01	0	94.2	19	0	23.4	0	40	0
4	0	1	0	47.8	-3.9	0	0	0	0	0
5	0	1	0	7.6	1.6	0	0	0	0	0
6	2	1.07	0	11.2	7.5	0	12.2	-6	24	0
7	0	1	0	0	0	0	0	0	0	0
8	2	1.09	0	0	0	0	17.4	-6	24	0
9	0	1	0	29.5	16.6	0	0	0	0	0
10	0	1	0	9	5.8	0	0	0	0	0
11	0	1	0	3.5	1.8	0	0	0	0	0
12	0	1	0	6.1	1.6	0	0	0	0	0
13	0	1	0	13.5	5.8	0	0	0	0	0
14	0	1	0	14.9	5	0	0	0	0	0

1. Bus Data

2. Line Data

Line	From	To	Length Km	R0 p.u	X0 p.u	R1 p.u	X1 p.u	B p.u	TAP
1	1	2	48	0.038383	0.117189	0.01938	0.05917	0.0528	1
2	1	5	48	0.107009	0.441742	0.05403	0.22304	0.0492	1
3	2	3	48	0.093066	0.39209	0.04699	0.19797	0.0438	1
4	2	4	48	0.11509	0.349211	0.05811	0.17632	0.034	1
5	2	5	48	0.112792	0.344378	0.05695	0.17388	0.0346	1
6	3	4	48	0.132717	0.338734	0.06701	0.17103	0.0128	1
7	4	5	48	0.02644	0.083401	0.01335	0.04211	0	1
8	4	7	0	0	0.414173	0	0.20912	0	0.978
9	4	9	0	0	1.101543	0	0.55618	0	0.969
10	5	6	0	0	0.499138	0	0.25202	0	0.932
11	6	11	50	0.188113	0.393932	0.09498	0.1989	0	1
12	6	12	50	0.24343	0.506645	0.12291	0.25581	0	1
13	6	13	50	0.131013	0.258006	0.06615	0.13027	0	1
14	7	8	0	0	0.348874	0	0.17615	0	1
15	7	9	0	0	0.21788	0	0.11001	0	1
16	9	10	50	0.063001	0.167357	0.03181	0.0845	0	1
17	9	14	50	0.251748	0.535501	0.12711	0.27038	0	1
18	10	11	50	0.162504	0.380404	0.08205	0.19207	0	1
19	12	13	50	0.437543	0.395873	0.22092	0.19988	0	1
20	13	14	50	0.338536	0.689271	0.17093	0.34802	0	1

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