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# A fault location method in distribution networks including DG

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**Abstract**

Finding and designing new methods for determining type and exact location of faults in power system has been a major subject for power system protection. One of the main capabilities that can improve the efficiency of new protection relays in distribution systems is exact fault locating. In this paper, a new approach for determining the exact fault type and location in distribution systems including distributed generation using MLP neural networks is presented. In the suggested method, after determining the fault type, by normalizing the fault current of the main source, the corresponding trained neural network has been activated and the exact location of occurred fault has been derived. The presented method has been implemented on a sample distribution network, simulated by DIgSILENT Power Factory 13.2, and its performance has been tested. The simulation results show high performance and accuracy of the method and substantiate that it can be used in modern heuristic protection schemes in distribution systems.

**Keywords:** Distributed Generation, Distribution System, Fault Location, Neural Network.

## Introduction

One of the important threats for distribution network equipments is the occurrence of short circuit fault and it has been a major challenge for power engineers. Recently, using of digital relays in power system protection causes capabilities of protection algorithms and schemes to be increasingly developed (Javadian & Haghifam, 2008; Navid Khalesi & Seyed Ali Mohammad Javadian, 2011; Seyed Ali Mohammad Javadian & Maryam Massaeli, 2011). In distribution systems, due to large variations of fault impedance, fault location problem has more importance and is more difficult to solve than transmission and generation systems (Rezaei & Haghifam, 2008). Furthermore, because of the low cost and significance of distribution network's equipments, it is not economically admissible in this case to design advanced protection schemes for these networks. On the other hand, the reliability of these networks can be greatly increased if the exact location of fault is determined using modified protection systems (Javadian & Haghifam, 2008).

Presence of distribution generation and applying renewable energies in distribution networks has been one of the other noticeable subjects for electrical engineers in recent years. DGs are small generation units with lower operational capacity in comparison with large power plants, which use clean and environmentally compatible energy resources to produce electricity. Due to small generation capacity, it is not economical to transfer their energy productions through the power transmission lines. So, DGs are generally connected to distribution systems (Barker & de Mello, 2000; Dugan & McDermott, 2000).

Presence of DGs in distribution systems has changed their simple and conventional radial configuration and results in more complexity of their operation, control and protection. Consequently, determining the accurate location of probable faults will be more important in distribution systems including DG (Farzanehrafat *et al.,* 2008).

Due to low fault impedance, it is not so intricate to find the fault location in HV transmission lines and is simply done by distance relays. On the contrary, we encounter various and relatively large impedances for faults in distribution systems which are extended in residential, urban and rural regions. With high amount of impedance and its extensive variations in distribution system, classic methods will not be appropriate to specify the fault location (Jiang *et al.,* 1999; Meshal *et al.,* 2003).

Optimization algorithms and artificial intelligence such as neural network, genetic algorithm, game theory, fuzzy logic, ant colony and simulated annealing have been widely used to solve optimization problems in engineering, so that simplicity and high speed in finding the solution are the results of employing these algorithms. Artificial neural network is one of the powerful methods to solve engineering problems such as classification and function approximation. High capability of neural networks as well as their simplicity results in increasing their usage for solving such problems (Ehsan & Soroudi, 2007).

In this paper, a novel technique to identify the type and accurate location of short circuit in distribution systems including DG is presented considering fault impedance using artificial neural networks. After introducing the MLP neural networks which are used in this study, the proposed method has been described in detail and finally, in order to illustrate the effectiveness of the suggested approach, the method is applied to a sample distribution network and the results are presented and discussed.

## MLP Neural networks

Multilayer Perceptrons are feed forward neural networks which consist of several layers of neurons with one layer as output layer and other ones as hidden layers. The number of neurons of output and hidden layers and their transfer functions are related to how the problem is defined. Usually, in technical and engineering

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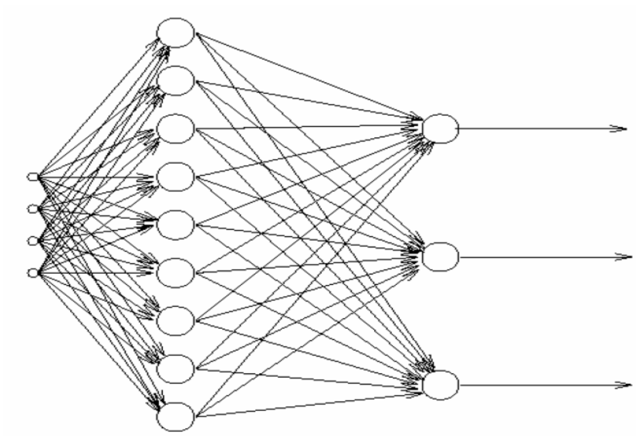
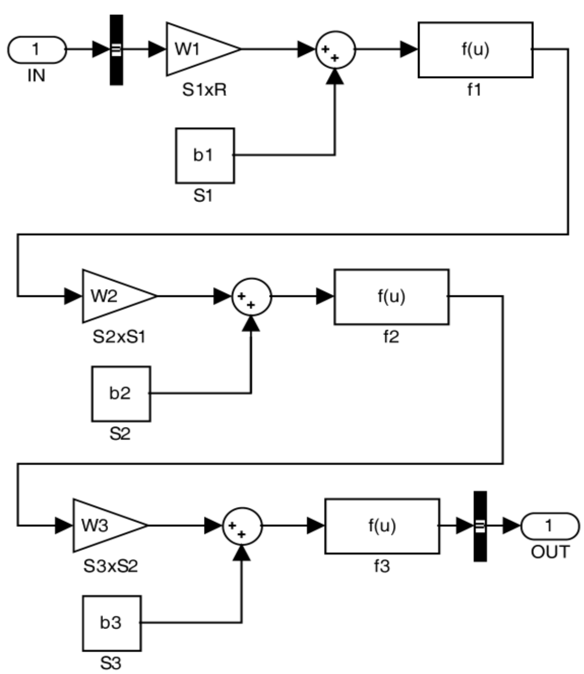
problems, MLP neural network with one output and one hidden layer is used. In this kind of problems, linear and Sigmund transfer functions are used for output and hidden layers respectively. A graphical representation of two-layer MLP which contains 4 inputs, 3 outputs and 9 neurons in hidden layer is shown in Fig.1. This network has the capability of classifying the inputs to 3 distinct classes with 4 characteristics.

*Fig. 1. General configuration of a 2-layer MLP*



The block-diagram of a 3-layer Perceptron network is depicted in Fig. 2. Each layer has one weighting and one bias vector. Multiplying of weighting vector and input vectors is added to bias vector and the result will be the

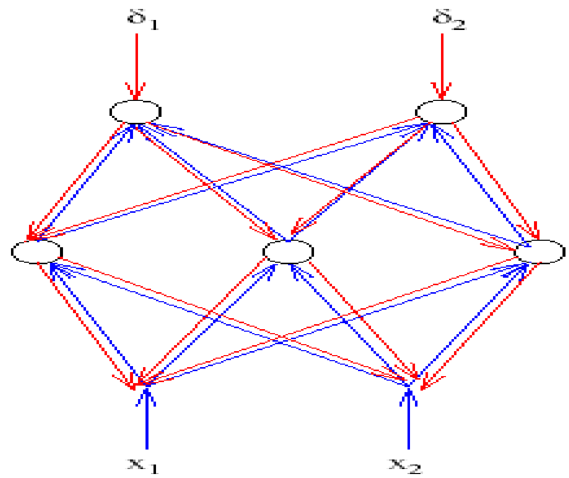
*Fig.2. The block -diagram of a 3- layer Perceptron*




input of transfer function. The output of the transfer function is the input of the next layer. In Fig.2, R is the numbers of inputs and $S_1$, $S_2$ & $S_3$ are the number of first, second and third layers' neurons respectively.

MLP neural networks train with the standard back propagation algorithm. The back propagation can be

*Fig. 3. Standard back propagation training method*




described briefly by Fig.3. and equation (1). In order to train the network and change the weights of neurons, in each iteration, the output of all neurons is calculated in forward path and the weights of neurons are changed in backward path using (1).

In back propagation, the gradient vector of the error surface is calculated. This vector points along the line of steepest descent from the current point, so we know that if we move along it a "short" distance, we will decrease the error. A sequence of such moves (slowing as we near the bottom) will eventually find a minimum of some sort. The difficult part is to decide how large the steps should be.

$$\begin{pmatrix} \text{Weight} \\ \text{correction} \\ \Delta w_{ji}(n) \end{pmatrix} = \begin{pmatrix} \text{learning} \\ \text{parameter} \\ \eta \end{pmatrix} \cdot \begin{pmatrix} \text{local} \\ \text{gradient} \\ \delta_j(n) \end{pmatrix} \cdot \begin{pmatrix} \text{input signal} \\ \text{to neuron } j \\ y_i(n) \end{pmatrix} \qquad \textbf{(1)}$$

Large steps may converge more quickly, but may also overstep the solution or (if the error surface is very eccentric) go off in the wrong direction. A classic example of this in neural network training is where the algorithm progresses very slowly along a steep, narrow, valley, bouncing from one side across to the other. In contrast, very small steps may go in the correct direction, but they also require a large number of iterations. In practice, the step size is proportional to the slope (so that the algorithms settle down in a minimum) and to a special constant: the learning rate. The correct setting for the learning rate is application-dependent, and is typically chosen by experiment; it may also be time-varying, getting smaller as the algorithm progresses.

The algorithm is also usually modified by inclusion of a momentum term: this encourages movement in a fixed direction, so that if several steps are taken in the same direction, the algorithm "picks up speed", which gives it the ability to (sometimes) escape local minimum, and also to move rapidly over flat spots and plateaus.

The algorithm therefore progresses iteratively, through a number of epochs. On each epoch, the training cases are submitted in turn to the network, and target; the actual outputs are compared and the error is calculated. This error, together with the error surface gradient, is used to adjust the weights and then the whole process repeats. The initial network configuration is random, and training stops when a given number of epochs elapses, or when the error reaches an acceptable level, or when the error stops improving (one can select which of these stopping conditions to use).

Back propagation algorithm progresses very slowly. So, because of the great amount of calculations in MLP networks and low convergence speed of the back propagation algorithm, several methods have been proposed to increase its convergence speed. Some of these methods are as follows: a). Gradient decent; b). Gradient decent with momentum; c). Gradient descent with momentum & adaptive learning rate; e). Gradient descent with adaptive learning rate; f). Levenberg-Marquardt; g). Quasi-Newton; h). Conjugate gradient.

**The fault location method**

It is assumed in the proposed method, that all 3 phase current of DGs of the network and the sub-transmission substation are accessible simultaneously and continuously. Regarding to improved and high technology of DGs, distribution automation systems and instruction of the connection of the DGs to distribution network (IEEE-1547 standard), measuring of output current of DG resources and their accessibility are some primary obligations of connection of DGs to these systems. So, taking the assumption of accessibility and usage of output current of DGs and sun-transmission substation will not impose any additional charge to design the protection system. The proposed method in this study consists of two parts which are recognizing fault type and determining fault location. These two parts are described in the following sections.

*Recognizing the fault type*

In order to determine the fault type, only the 3 phase current of the main source is used. At this point, there is no need to ANN and it can be determined with normalizing 3 phase output current of feeding substation. To normalize the mentioned currents, the following equation is used:

$$I_{normal} = \frac{I}{I_{\max}} \qquad (2)$$

*Table 1. Normalized current vector of the main source for different fault types*

| Fault Type | | $I_a$ | $I_b$ | $I_c$ |
|---|---|---|---|---|
| 1-phase | Ag | 1 | 0 | 0 |
| | Bg | 0 | 1 | 0 |
| | Cg | 0 | 0 | 1 |
| 2-phase | AB | 1 | -1 | 0 |
| | AC | 1 | 0 | -1 |
| | BC | 0 | 1 | -1 |
| 2-phase to ground | ABg | 1 | 1 | 0 |
| | ACg | 1 | 0 | 1 |
| | BCg | 0 | 1 | 1 |
| 3-phase | ABC | 1 | 1 | 1 |

Where

I: phase current

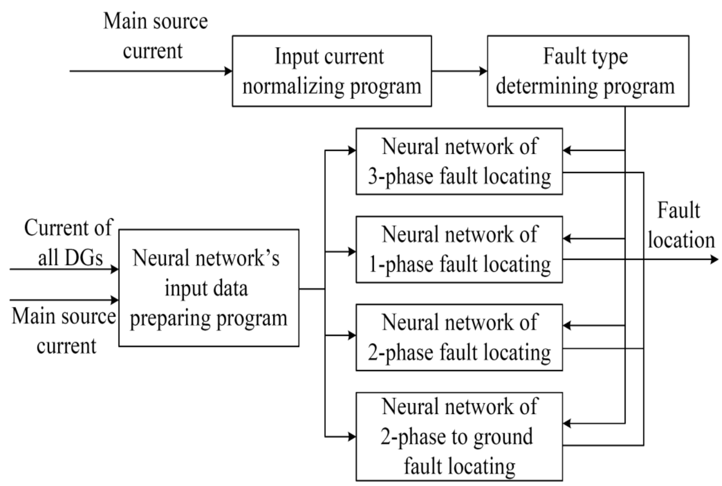
Imax: maximum phase current

Fault type can be determined using (2) and Table 1.

*Determining fault location*

After recognizing the fault type, its location should be determined. In this paper, MLP neural network is used for specifying exact location of the fault. The outline of the proposed method is shown in Fig.4.

*Fig. 4. The outline of the proposed method*




After recognizing fault type by its corresponded unit, the trained neural network of this kind of fault is activated and receives the input data which has been prepared by the input data preparation program. The output of the neural network will be the fault distance from all DGs and the main source.

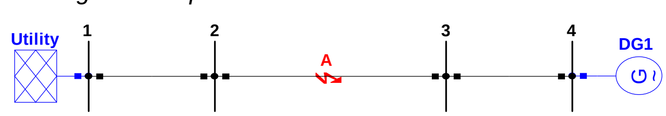
As mentioned previously, the major problem of fault locating in distribution networks is fault impedance. For the purpose of minimizing the effect of fault impedance to the output of neural network, appropriate characteristics have to be defined for neural network. Proportional relationship between injected fault current of DGs and feeding substations to each other is taken as the input of neural network in this study.

Injected fault current of each DG can be calculated using (3).

$$I_f = \frac{V}{Z_{th}} \qquad (3)$$

Where V is power supply terminal voltage and $Z_{th}$ is the equivalent Thevnin impedance of the network. For instance, in the network depicted in Fig.5, in the case of zero-resistance short circuit in A, equivalent impedance of DG and network is:

*Fig. 5. A simple distribution network with one DG*



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$$Z_{DG} = Z_{34} + Z_{3a} \qquad (4)$$

$$Z_s = Z_{12} + Z_{2a} \qquad (5)$$

Where:

$Z_{12}$ impedance of transmission line between bus 1 and bus 2; $Z_{34}$ impedance of transmission line between bus 3 and bus 4; $Z_{3a}$ impedance of the part of the transmission line between bus 3 and point A (fault point); $Z_{2a}$ impedance of the part of the transmission line between bus 2 and point A (fault point);

In this network the proportion of short circuit current of the network to short circuit current of the DG is

$$\frac{I_S}{I_{DG}} = \frac{Z_{34} + Z_{3a}}{Z_{12} + Z_{2a}} \qquad (6)$$

Assuming nonzero-impedance short circuit at point A, the mentioned relation is:

$$\frac{I_S}{I_{DG}} \approx \frac{Z_{34} + Z_{3a} + Z_f}{Z_{12} + Z_{2a} + Z_f} \qquad (7)$$

which is approximately the same as (6). So, using this proportion, i.e. the relation of injected fault current of various resources as the input of the NN, the impact of the fault impedance will decrease to its lowest amount. It can be observed that this method is applicable on distribution networks which include DG. This means the proposed method is only worthwhile for using in those networks and cannot be applied for fault location in conventional distribution systems.

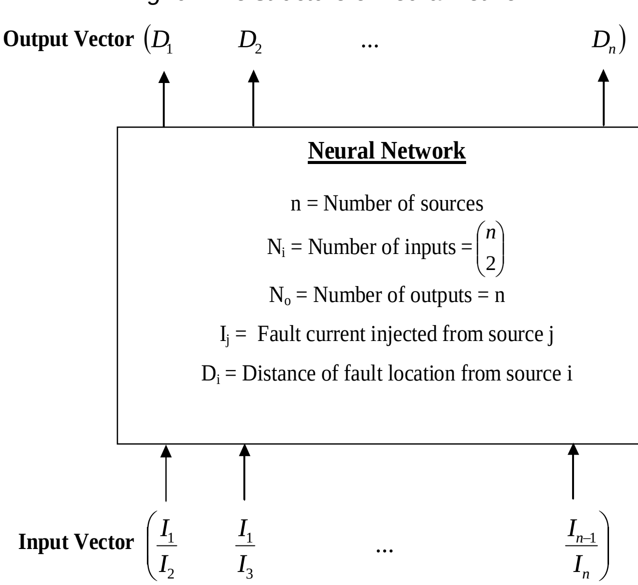
Furthermore, it is important to be mentioned that by increasing the number of DGs connected to distribution system, the accuracy of fault locating of neural network will be improved due to growth of number of its inputs. For example, in the case of one DG in the network only one input can be used for training the neural network while in the case of n DG resources connected to the network, the number of inputs of neural network is:

$$N = \binom{n}{2} \qquad (8)$$

Where n is the number of suppliers of fault current (one the network and n-1 DG resources). The number of outputs of neural network is n which is equal to the number of fault current suppliers and each output uniquely determines the distance of the fault from its power supply. So, the structure of neural network used in this paper is graphically shown in Fig.6.

In order to avoid the complexity of the neural network, only one hidden layer is used for its constructing, while the neurons number is related to the modifying conditions and cannot be specified precisely. It has to be mentioned here that in a particular problem, the number of neurons in the hidden layer can be determined with try-and-error method. The number of output layer neurons is equal to the number of outputs. Linear type and hyperbolic tangent type transfer function is considered for output and hidden layer neurons, respectively, and Levenberg-Marquardt algorithm has been used for neural network training method.

*Fig. 6. The structure of neural network*




## Simulations

In this paper for modeling and simulation of sample distribution network and extracting necessary data for training of neural network, DIgSILENT Power Factory 13.2 is used and simulation of neural network is done in MATLAB as well.

A 22-bus, 20 kV distribution network with a 3.5MVA synchronous generator connected to buses 22 and a 4.5MVA synchronous generator connected to buses 4, is considered as a test system for simulations. Single line diagram of this network is illustrated in Fig.7.

*Fig. 7. The studied distribution network*

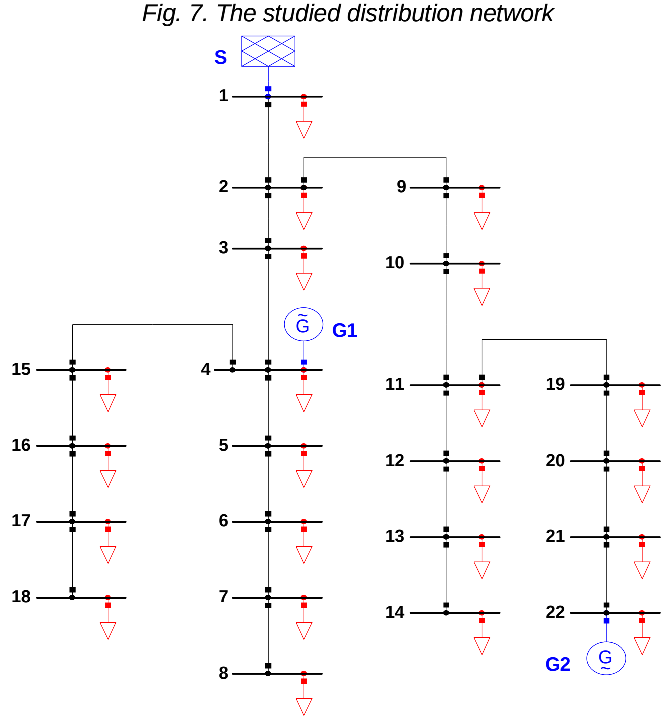


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*Fig. 8. Training result of neural network for 3-phase faults*

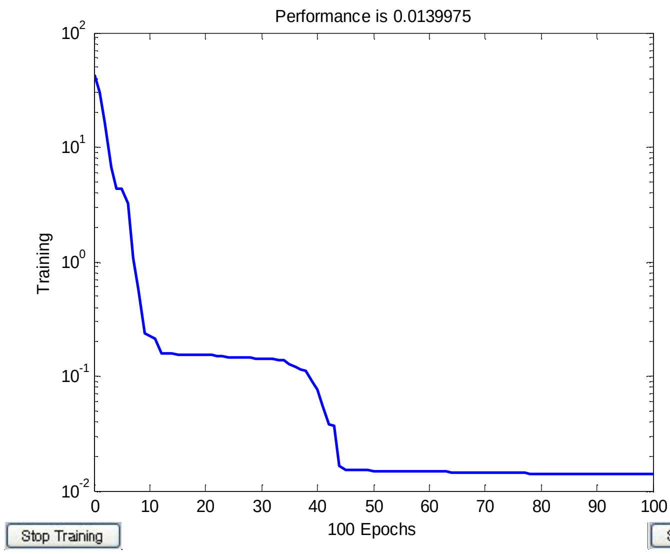



*Fig. 10. Training result of neural network for 2-phase faults*

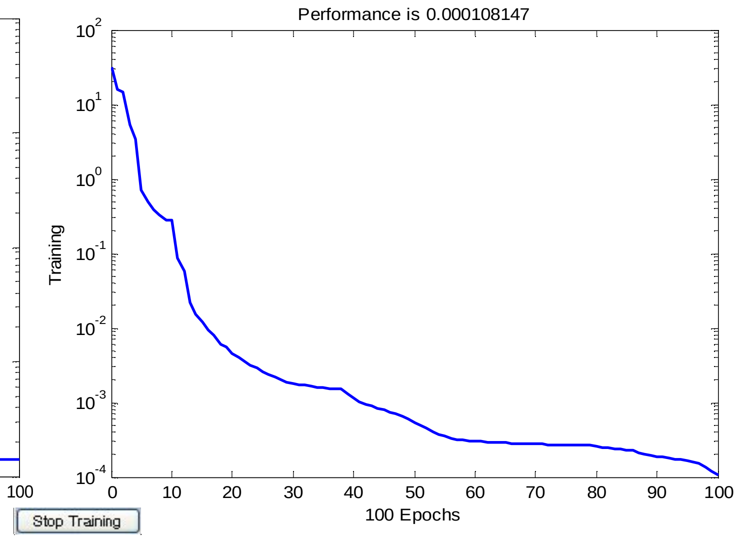



*Fig. 9. Training result of neural network for 1-phase faults*

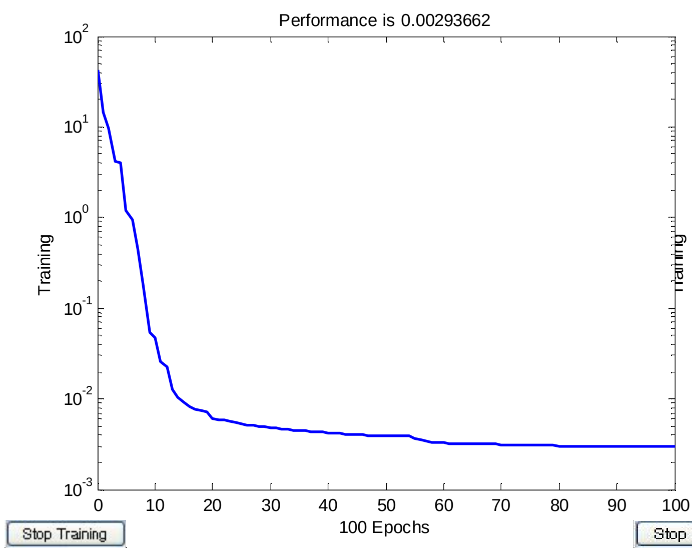
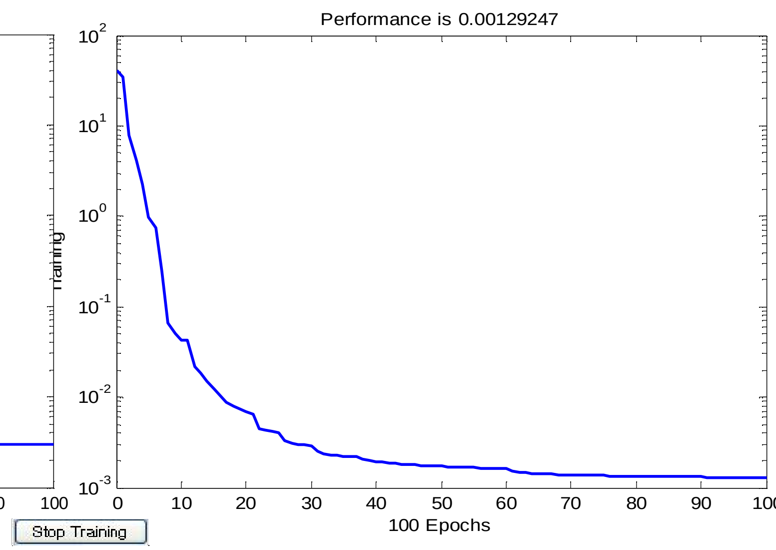



*Fig.11. Training result of neural network for 2-phase to ground faults*




In order to prepare the required data for training the neural network, all types of faults in the system in each 100 meter and with 0, 50, 100, 150 ohm fault impedance is simulated and the output current of all power supplies are exploited. Training results of all neural networks are shown in Fig. 8 to 11. Neural network structures for each fault type as well as their training error are tabulated in Table 2.

*Table 2. Structure and error of trained neural networks*

| Fault Type | NN Structure | MSE |
|---|---|---|
| 3-phase | [ 3 6 3 ] | 0.0139975 |
| 1-phase | [ 3 5 3 ] | 0.00293662 |
| 2-phase | [ 3 7 3 ] | 0.000108147 |
| 2-phase to ground | [ 3 7 3 ] | 0.00129247 |

According to the results, the highest error of trained neural networks is 14 meters. Regarding to 1km length of distribution lines in studied network and knowing that recognizing the faulted line is the final goal of protection systems in distribution networks, the deviation in proposed method is passable and quite satisfying and can be used for designing the intelligent protection systems for distributed networks in presence of DGs.

**Conclusions**

A new method using MLP neural network to determine the type and location of fault in distributed networks is presented in this paper. In the method, to reduce the impact of fault impedance to determine the fault location, proportion of injected power supplies current is taken into account and used as the input of neural network. Having normalized the fault current injected form feeding substation, the fault type is recognized and afterwards the trained neural network related to this fault is used to specify the distance of the fault from each power supplies. The proposed method was implemented on a sample distribution system simulated in DIgSILENT Power Factory and the required data for training the neural networks is extracted. Simulation results demonstrate the power, effectiveness and great accuracy of the method and confirm its acceptable capability to be used for designing the intelligent protection schemes in modern electrical power distribution systems.

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