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Optimized artificial neural network method for underground cables fault classification

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ABSTRACT

The electrical power network is the biggest system made by humans in the world. With increasing the demand for this type of energy, several problems have emerged in an electrical power network. In this condition, new and complicated problems have emerged in these large networks. One of the most important problems in these networks are the occurred faults in underground cables. This study investigates the efficient approach for detecting these faults with high accuracy. In this study, we consider four different states in cables that are normal conditions, one phase fault, two-phase fault, and three-phase fault. This study proposes the application of multilayer perceptron (MLP) neural networks as a classifier. MLP neural networks are powerful and efficient classifiers among other classifiers. In the MLP, the parameters of the number of hidden layers and the number of neurons have a high effect on its performance. These parameters must be selected by accuracy. Thus this paper proposes the application of an imperialist competitive algorithm (ICA) for finding the optimum value of these parameters. Simulation results show that the proposed intelligent method has very good performance and accuracy.

1. Introduction

There are many advantages in the use of underground cables. But the usage of this technology has some important difficulties. One of the most important associated difficulties is if a fault occurred in these cables, the human operator cannot see the error shape or location. This issue led to large problem in power networks. If the distribution system had a fault, the human operator must rapidly identify that occurred fault and remove that fault.

In underground cables three different faults can be occurred. They are one phase fault, two phase fault and three phase fault. In normal condition the network has no fault. For eliminate the human operator and provide the effective and powerful method for detecting the faults numerous techniques can be used. One the most popular classification methods are the artificial neural networks. This technique mimics the human body's strategy in learning of various works in real world (Xiao et al., 2017).

The artificial neural networks have many applications in many fields such as breast cancer detection, electro cardiogram classification (ECG), EEG classification, control chart patterns recognition (CCP), robot control systems, stock market prediction, nonlinear and chaotic signals forecasting, clustering, proportional integral derivative controller tuning, optimization problems, communication applications, power electronic systems and many other applications (Tan et al., 2015; Li and Jian, 2015).

One the most effective and powerful types of artificial neural networks is the MLP neural networks or MLPNN. This kind of artificial neural networks is made of multi layers. These layers are input layer, hidden layer or hidden layers and output layer. The detailed description about MLPNN is presented in the following sections. As mentioned before, the number of hidden layers and number of neurons in MLPNN have very high impact on the performance of this type of artificial neural network. For this reason in this study we proposed an intelligent method for finding this parameter. The proposed method uses the imperialist competitive algorithm (ICA) optimization method for optimizing the MLPNN structure. ICA is the powerful and rapid optimization algorithm that its performance and capabilities has been proven in many literatures.

The rest of paper is organized as follow. Section two describes the MLP neural network. Section three present the ICA and optimization method. Section four presents computer simulation results. Section five discuses and concludes the presented and simulated concepts in the paper.

2. MLP neural network

Artificial neural networks are the intelligent model of human body system. This concept mimics the human body system in learning the new subjects and manners. The artificial neural networks have many models such as radial basis function neural networks (RBF), probabilistic neural networks (PNN), MLPNN, concurrent neural networks and many other models. Among these models, MLP neural network has excellent in classification tasks. This type artificial neural network has been introduced by Perceptron. The structure of MLP neural network has been shown in Fig. 1.

The MLP neural network has multi-layer. The first one is input layer. The last one is output layer. Between the input layer and output layer there is one or multi hidden layer. The relation between the layers is done by weights and bias values. In each neuron there is activation function. This activation function has several types such as linear activation function, tangent sigmoid activation function, logarithm sigmoid activation function. The type of activation function has high effect on performance of MLP neural network.

In MLP neural network, the number of neurons in input layer and output layer is fixed and related to dimension of input signal

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dimension and target matrix dimension. But the number of hidden layers and the neurons in hidden layers are free parameters and must be determined by used. More details regarding the MLP neural network can be found by Hagan and Menhaj (1994).

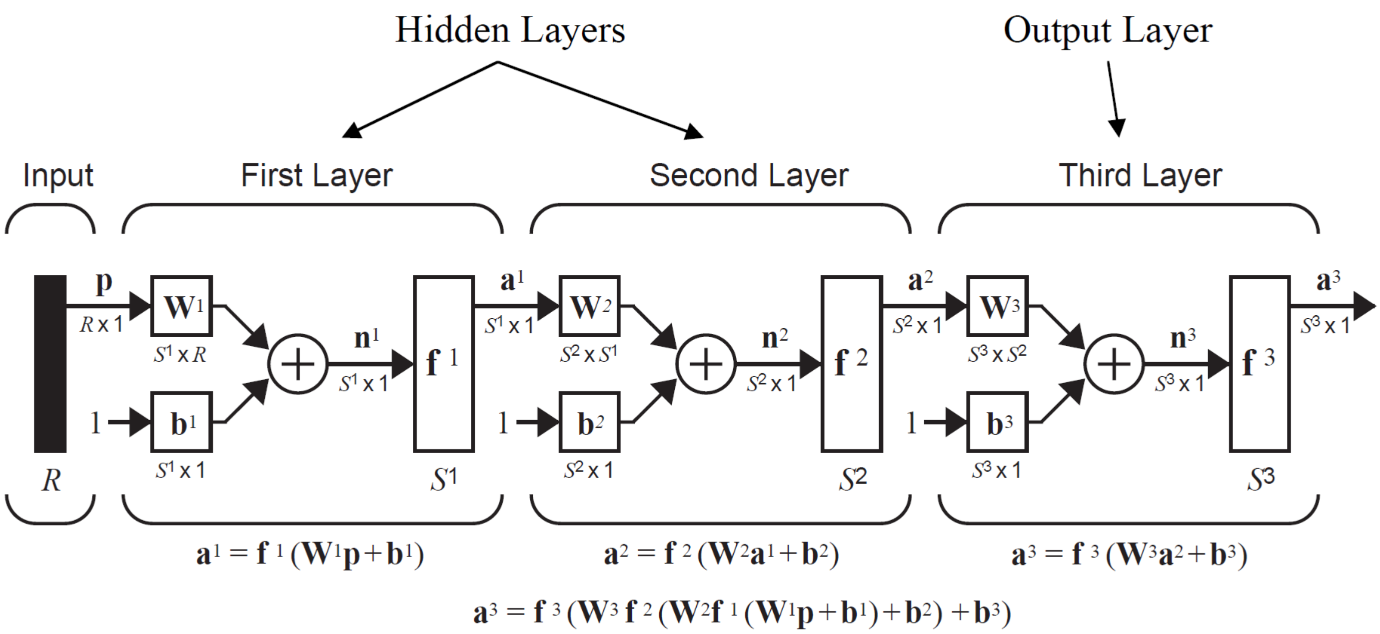

Fig. 1. The main structure of MLP neural network.

3. Proposed system

3.1. Optimization algorithm

In last decade several nature based optimization algorithm have been emerged. These algorithms mimic the animals and human manner in searching the best food source or location. Some of these algorithms are: Genetic algorithm (GA), particle swarm optimization (PSO) algorithm, ant colony optimization (ACO) algorithm, imperialist competitive algorithm (ICA), Cuckoo search (CS), Cuckoo optimization algorithm (COA), Bees algorithm (BA), Honey bee mating optimization (HBMO) algorithm, Artificial bee colony (ABC) and many other nature based algorithms or their modified versions (Atashpaz et al., 2008; Karaboga, 2009). In each optimization algorithm, two main criteria are important: The finding of global solution vicinity or exploration and the main global solution finding exactly or extraction. Each optimization algorithm that has these two main standards will be good optimization algorithm. Many of the proposed method that has been introduced are week in one of the mentioned standards. For example the PSO algorithm has well exploration capability but doesn't have well extraction capability. In contrast, GA has very well extraction capability and week exploration capability. Also many of these optimization techniques have very operators and computational efforts.

In science of swarm intelligence, imperialist competitive algorithm is an iterative optimization technique that inspired from human manner in social issues. Similar to other nature based optimization algorithms, imperialist competitive algorithm don't need to gradient information of fitness function. This feature gives this ability to these algorithms to don't trap in local minima. Imperialist competitive algorithm is more similar to genetic algorithm. In both optimization algorithms, the human enhancement is modeled. In genetic algorithm the human improvement from genetic view is studied, but in imperialist competitive algorithm the human enhancement in social and politics issues is studied. In other nature based optimization algorithms the manner of animals for food searching in nature is modeled. In Fig. 2, the main structure of imperialist competitive algorithm is illustrated.

Imperialist competitive algorithm is a swarm intelligence algorithm that firstly presented by Naderi and Yazdani (2014). Since emerges of this optimization algorithm, it is applied in many optimization problems (Duan and Huang, 2014; Afonso et al., 2013). ICA is based on imperialist contest. These algorithm efforts to model the human policy and imperialist countries in attain and govern high nations and countries. The imperialist countries use the different resource of occupied countries. These resources may be mine, underground source of energy and many other source of energy. Also the imperialist countries attempt to change the culture and language of weak countries. Also in this algorithm, the imperialist countries contest with them to increase their power. The imperialist competitive algorithm starts with chancily primary population in search space. In this algorithm, countries have chromosomes roles in genetic algorithm or particles in particle swarm optimization algorithm. In first iteration the fitness function is calculated for these initial countries and the most powerful countries are selected as imperialist countries. The remaining countries are colonies and must divide among the imperialist countries. In this step a competition starts among the imperialist countries to attain more colonies. The more powerful imperialist has high chance to attain more colonies. After the finishing the competition among the imperialist countries, the empires composed. This procedure is depicted in Fig. 3. The most powerful imperialist country has more colonies and therefore has more power in the world.

When the completion stopped and the empires took place, the weak countries or colonies attempt to approach their associated imperialist country. This procedure is illustrated in Fig. 4. In this movement the colony doesn't completely arrive to its imperialist. The mathematical modeling of this movement is as follow:

$$\alpha \approx U(0, \beta \times S) \quad (1)$$

In final step of this algorithm, the most powerful empire will take all the colonies and empires. In this state only one empire will be in the world and the optimization will stop. The main steps of ICA are as follow:

1. Generate initial population (countries) in search space.
2. Evaluate fitness function for each country.

3. Select the empires and colonies.
4. Do the movement of colonies to imperialist country as shown in Fig. 3.
5. Evaluate of each empire power.
6. Eliminate the weakest empire and divide it among other empires.
7. Check the empires number. If there is only one empire, then stop the algorithm. Else go to step 4.

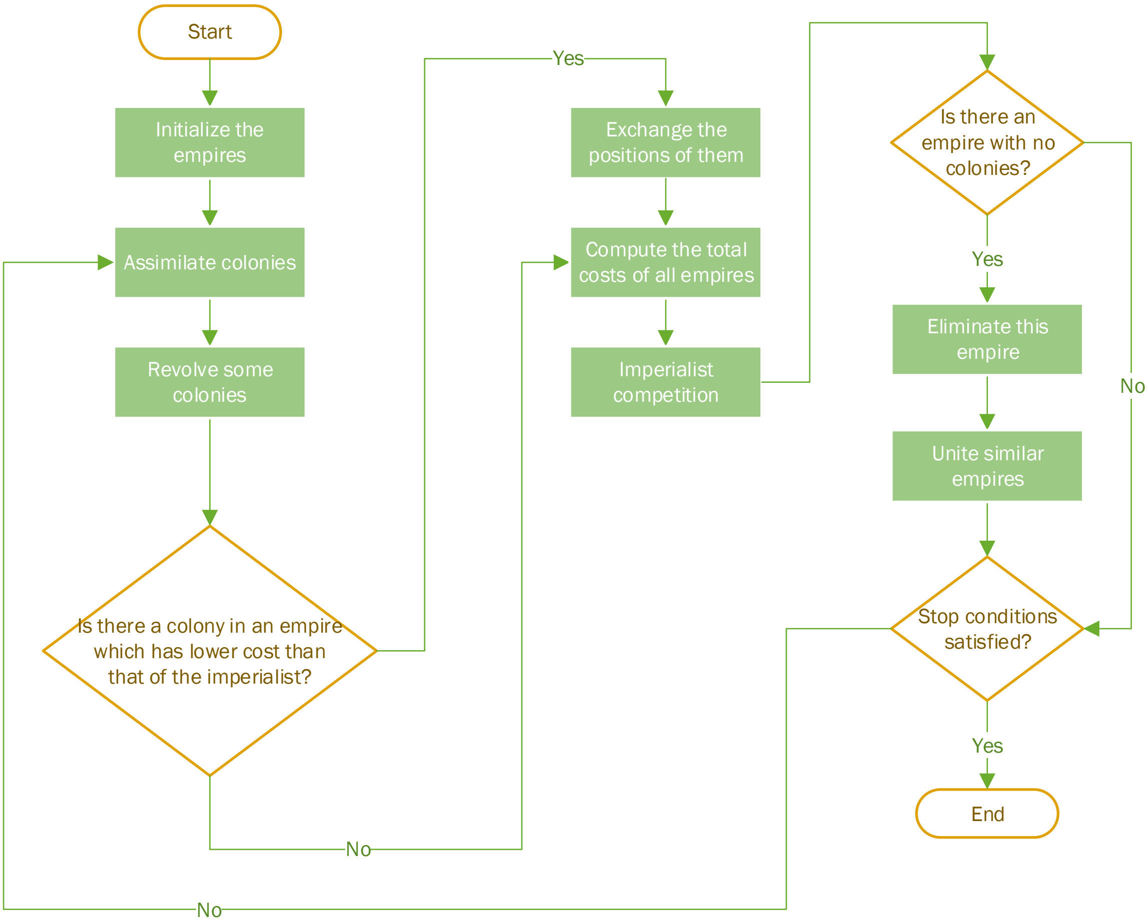

Fig. 2. The main structure of imperialist competitive algorithm.

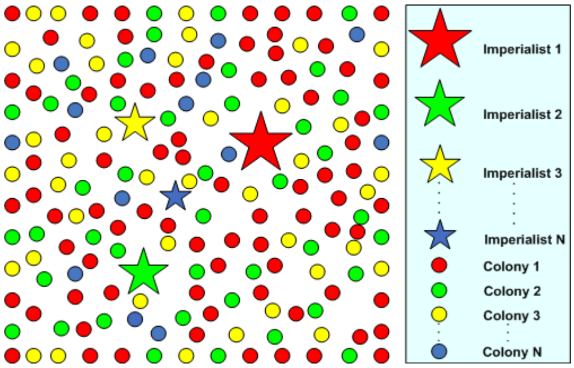

Fig. 3. Composition of empires in ICA.

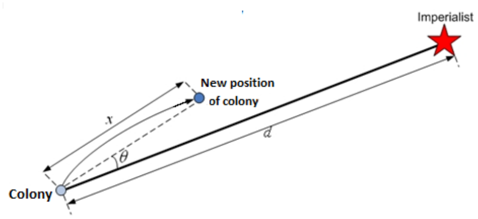

Fig. 4. Moving colonies toward their relevant Imperialist.

3.2. Proposed method

In this paper an intelligent method has been proposed for underground cable faults detections. As mentioned in underground cables there are four different conditions. The first one is normal condition that in this state there is no fault in power system. The second one is one phase fault. The third one is double phase fault. The forth one is three phase fault. The proposed method uses MLPNN as classifier. As mentioned in the MLPNN the number of hidden layer and number of neurons have high effect on performance of system. Thus in the proposed method optimization algorithm is applied to find the optimum value of these parameters. The pseudo code of proposed method is shown in Fig. 5.

1.Initialize ICA algorithm parameters
2.Generate initial population in search space
3.Evalute the MLPNN with initial population
4. Select the empires
5. Do competitive among empires
6. Do movement of colonies
7. Do revolution
8. Check stopping criteria, if it is don't satisfied, go to step 3.
9. End

Fig. 5. Pseudo code of proposed method.

The he sample country is shown in Eq. 2. In each generated country, if the first parameter is 1, then the composed MLP network has just one layer. In this network, the number of neurons in hidden layer determined by second parameter in generated country. If the first parameter in generated country is 2, then the composed MLP network has 2 hidden layers. In this network the number of neurons in hidden layers determined by 2nd and 3rd parameters in country.

$$samplecountry = [Number\ of\ hidden\ layers, Number\ of\ neurons\ in\ 1^{th}\ layer \ldots\ldots, Number\ of\ neurons\ in\ 3^{th} layer\ ] \quad (2)$$

The 2nd parameter determines the number of neurons in first hidden layer and the 3rd parameter determines the number of neurons in second hidden layer. Also if the first parameter in generated is 3, then the composed MLP network has 3 hidden layers. In this network the number of neurons in hidden layers determined by 2nd, 3rd and 4th parameters in country. The 2nd parameter determines the number of neurons in first hidden layer, the 3rd parameter determines the number of neurons in second hidden layer and the 4th parameter determines the number of neurons in third hidden layer. This procedure determines the optimal structure of MLP network. This system will have good performance.

4. Simulation results

In this section the performance of proposed method is evaluated. In underground cables there are four different conditions. The first one is normal condition that in this state there is no fault in power system. The second one is one phase fault. The third one is double phase fault. The forth one is three phase fault. Figs. 6- 9 show these conditions.

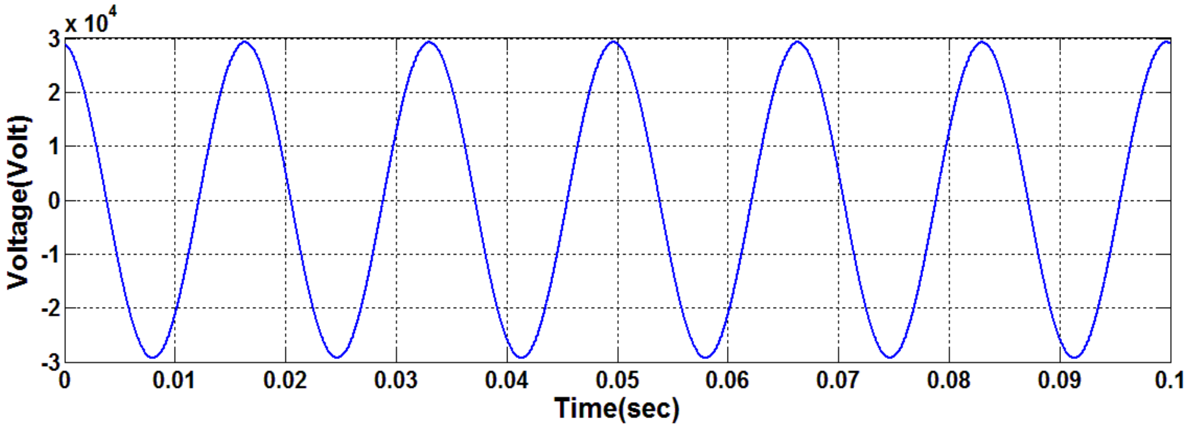

Fig. 6. Voltage signal of normal state.

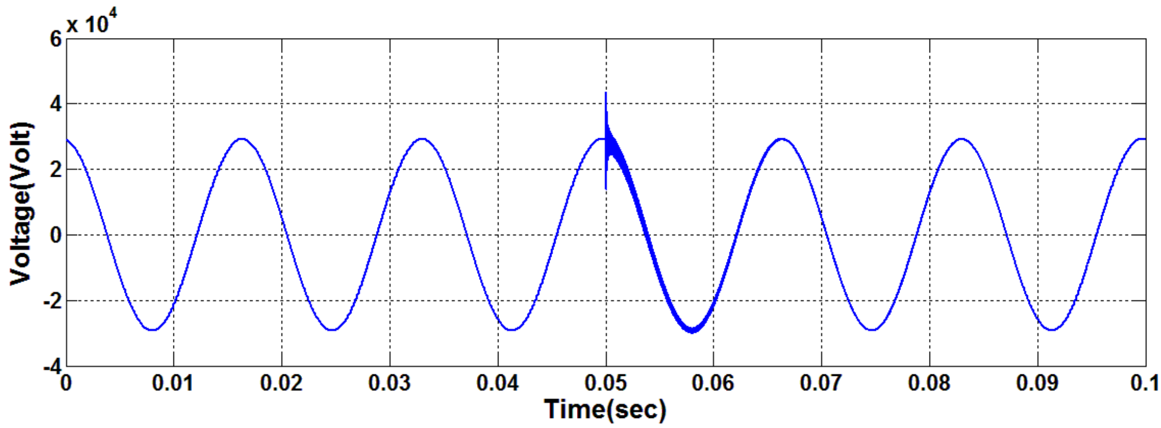

Fig. 7. Voltage signal of single phase fault state.

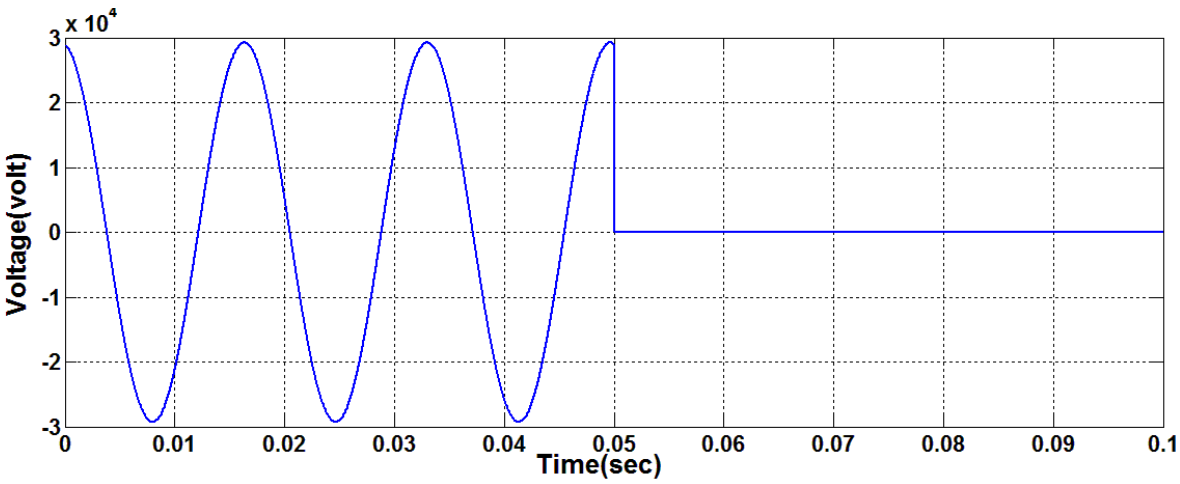

Fig. 8. Voltage signal of double phase fault state.

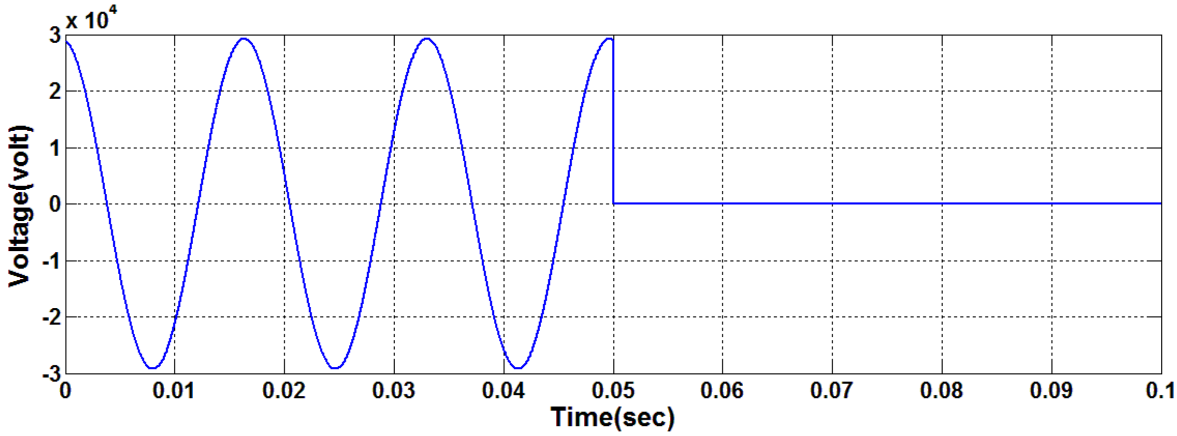

Fig. 9. Voltage signal of three phase fault state.

In the ICA algorithm the control parameters have very vital role in its speed and convergence. For this purpose we must select these parameters by accuracy. In ICA the number of countries (n) is indicates the number of all the countries that spread in search space in first step. If the value of n will be high, then the simulation time will be high. Also if the value of n is low, then the probability the convergence of optimization algorithm will be low. Thus we will select the n by accuracy. Table 1 shows the ICA parameters.

Table 1
ICA parameters.

Parameter	Value
Number of colonies	30
Number of Imperialists	4
β	0.02
θ	30
Number of iterations	100

The training parameters and the configuration of the MLP used in this study are shown in Table 2. In the MLP neural network the training algorithm has very effect on its performance. Therefore several training algorithm is used to enhance the recognition accuracy.

Table 2
MLP architecture and training parameter.

The number of layers	2
Number of output neurons	6
Learning algorithm	Back-propagation with momentum Backpropagation LM SCG CGBFR BFGSQB OSS
The initial weights and basis	Random
Activation function (Hidden layer)	Tangent-sigmoid
Activation function (Output layer)	Linear

First the MLP without optimization is investigated. The number of hidden layers is determined as one. The various numbers for number of hidden layer neurons is investigated. The obtained results are shown in Table 3. As it is depicted in Table 3, using various training algorithms and input data, the highest accuracy is 98.8%, which is achieved by SCG training algorithms. For detail investigation the effect of number of neurons, Table 4 shows the experiment results. In this experiment the MLP network by SCG training algorithm is used.

Table 3
Recognition accuracy different systems using row data.

Training algorithm	RA (%)	Number of hidden neurons	Run time (Sec)	Standard
Back-propagation with momentum	95.03	17	5	6.8
RPROP	97.67	20	2	2.3
LM	96.43	24	18	9.5
SCG	**98.8**	**14**	**12**	**1.6**
CGBFR	95.64	18	3	12.8
BFGSQB	96.34	32	118	6.76
OSS	97.02	19	2	4.9

Table 4
The investigation number of neurons effect by SCG training algorithm.

Number of hidden neurons	Recognition accuracy (%)	Time (Second)
5	95.2	9
6	95.3	10
7	95.4	10
8	96.3	10
9	97.7	11
10	98.1	11
11	98.2	11
12	98.4	11
13	98.4	11
14	**98.8**	**12**
15	98.2	12
16	98.3	12
17	98.1	12
18	98.4	12
19	98.5	12
20	98.2	12
21	97.7	12
22	97.9	12
23	*98*	12

24	98.1	12
25	97.7	12
26	97.6	12
27	98.1	12
28	97.8	12
29	96.5	12
30	96.4	12

In Fig. 10, the effect of neurons in hidden layer is illustrated. It is clear that the number of neurons don't have straight relation with recognition accuracy. Thus the number of neurons must be selected intelligently.

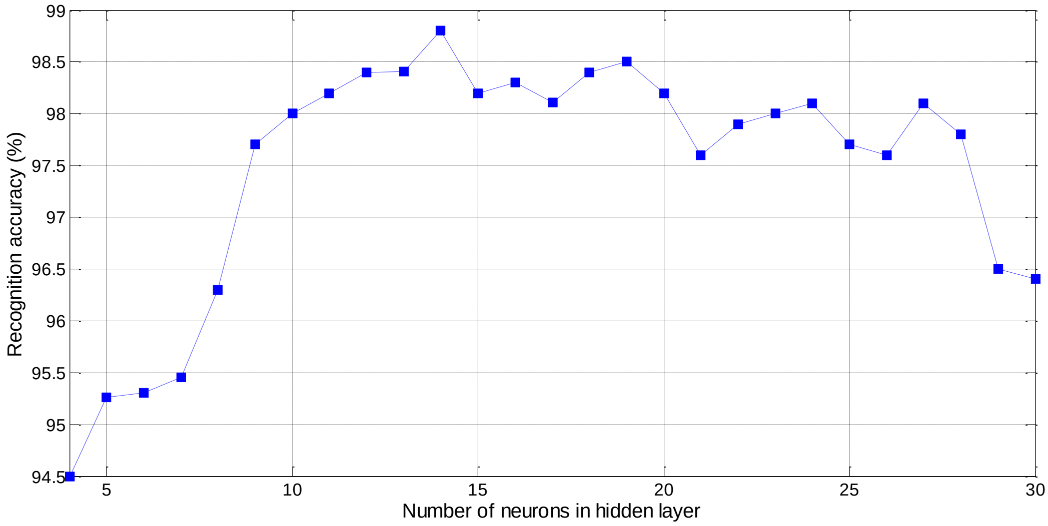

Fig. 10. The investigation number of neurons effect by SCG training algorithm.

In next step, the ICA is applied to find the optimum structure of MLP network. In this experiment, the optimization algorithm is run 10 time and the obtained results are shown in Table 5. The obtained results demonstrate that the optimization has very effect on MLP performance.

Table 5
The performance of proposed system.

Row	Number of layers	Number of neurons			Recognition accuracy (%)
		Layer 1	Layer 2	Layer 3	
1	3	28	11	30	99.5
2	**3**	**25**	**15**	**17**	**99.6**
3	3	28	2	28	99.5
4	2	9	11	-	99.5
5	3	8	4	11	**99.6**
6	2	8	15	-	**99.6**
7	2	18	7	-	99.5
8	3	9	13	17	**99.6**
9	3	8	14	11	**99.6**
10	2	20	15	-	**99.6**

5. Conclusion

In this paper the fault detection in underground cables is investigated. Underground cables are very popular and vastly used in power network. This type of power distribution system has numerous benefits and advantages. But there is one prominent disadvantage in this technology. In underground cables there is no systematic way to detect and identify the type of has occurred. In secure power network system, the occurred fault must identify rapidly and removed. For this purpose in this paper an intelligent technique has been proposed for fault detection in underground cables. The proposed method has two main sections: The classifier section and the optimization section. The simulation results show that the proposed method has good performance. The MLPNN can detect the underground cables by accuracy of 98.8% and the proposed method can detect the faults by accuracy of 99.6%. This results show that the optimization enhance the performance of MLPNN significantly.

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