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Electric Power Cable Fault Recognition via combination of wavelet transform and optimized artificial neural network by using bees algorithm

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Abstract

Fault detection and diagnosis of underground cables is one of the basic parts of maintenance and repair of power cables, and without using of modern diagnosis approaches, the electric power distribution companies cannot provide reliable services to industries and public consumptions. So, power cable diagnosis requires widespread support and attention. In this paper by means of case based methods and also fault detection and fault classification algorithms, the common faults in the underground cable transmission system will be detected. The neural network has been used for classification, in the proposed method. Also, to optimize the performance of neural network, the wavelet transform as effective input, and the bee algorithm for finding the optimal values of neural network control parameters have been used. The simulation results show that the proposed method has high detection capability and shows good performance, so that can separate about 100 percent of faults successfully. For this reason, the overlap matrix has been presented in analyses.

Keywords: Wavelet transform, MLP neural network, RBF neural network, Bee algorithm, Overlap matrix.

1. Introduction

Power cables are one of the important equipments of electrical power transmission and distribution systems. Because of importance of power cables in electrical systems, theses expensive and critical equipments have drawn attention of many researchers from various

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aspects. Many researchers have been done in the fields of design, application and protection of power cables based on the different aspects of their application, from production to operation stage. The overhead lines combined with underground lines are one of the most complicated parts in the electrical power systems that depends on the reliable distribution and transmission system. As we know, the faults in the overhead lines occurs by events such as lightning, falling trees, the dust and salt on polluted insulators, ice and snow on insulators and so on; Whereas underground faults are as follows[1, 2]:

a) Series faults which a cable disconnect without breaking its insulation.

b) Shunt faults which the cable insulation breaks, without cable disconnection.

The simultaneous methods for fault location in overhead and underground lines are classified in two parts [1, 2]:

a) Methods based on measurement of lines impedance called phasor algorithm which only use fundamental components of measured signals.

b) Methods based on measurement of the signals produced by faults.

In the systems consisting of an overhead line combined with an underground cable, the most important fault location problem is inequality of the positive and zero sequence impedances of underground and overhead cables. Besides, the impedance of underground cable is 10 percent of overhead cable that may leads to error in estimating the fault location [3]. Using of underground cables has some problems besides their many advantages. Lots of the disadvantages are because the fact that accidental fault in the underground cables is not easily discoverable. The other disadvantage of this system is that the relays cannot detect the single line to ground fault because in the case of contacting a phase to the body of the tunnel, the fault current is much less than the relay trip current. So the protection relay cannot detect the fault and the fault continuously remains in the system. This is dangerous when the second

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phase connects to the ground, so two phase to ground fault happens and the electrical system disconnects by relays trip. This electrical system disconnection in some regions like industrial towns or critical centers can causes irreparable damages [3]. So it is necessary to detect the faults in the underground transmission systems by appropriate device and by proper speed and accuracy. The fault location in power lines is necessary and critical for economic performance of power system. It is necessary to note that accurate and optimized fault location by proper monitoring, can cause faster repair, improve the system performance, decrease the costs of operation and also saves the time and decrease the costs of searching in bad and unfavorable conditions (like bad weather condition or fault location in difficult places like inside the ground) considerably [1, 2].

One of the important topics in power cables performance and proper and optimized detection of fault is their situation monitoring. Today, by considering this important point that the power cables are designed and produced to use in different voltage levels, and also the great importance of power cables for reliable transmission of electrical energy, and on the other hand, development of computer technologies and using them in the monitoring systems, the new methods have been proposed to monitoring of power cables. As it has been mentioned before, fault detection and accurate fault location, will be simplified the fast repair of the cables, increased the access to the network and decreased the operating costs [3, 4].

The most important targets of power cables monitoring is as follows:

a) Increasing the reliability of power cables by fast fault detection.

b) Increase longevity of power cables in electrical systems due to appropriate operation by means of cable situation monitoring and predicting possible defects.

c) Decreasing operating costs of cables and their equipments and dependent systems.

d) Increasing the automatic monitoring and operation or equipment management.

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Many studies have been done to evaluate and diagnosing these problems and faults in power cables. In [5, 6], a method has been proposed to detect and classify the fault for medium voltage underground cables of urban distribution network by means of neural network. For teaching the neural network, the parameters such as fault type, fault impedance, fault starting angle and magnitude of system load has been considered. A sample distribution network has been simulated in PSCAD/EMTDC software and then, by means of these parameters, the neural network has been taught and then tested. The results showed that the neural network can detect the fault with high accuracy.

In [7], a method has been proposed for underground power cables fault detection, based on finite element method. In this method firstly the power cables with all of their belongings such as shield, insulators, and conductors and so on is modeled and then a failure in the cable or short circuit or insertion the air bubbles or water tree phenomenon is applied. After this stage, the problem is analyzed by finite element method. Finally, based on the temperature variation with respect to time, and by considering the diagram slope, the fault detection is performed. The other methods for fault detection and fault location in power cables, is the traveling wave based methods [8, 9]. This method is used for fault location. This method is based on this fact that during fault, two kinds of waves, the backward and the forward waves, are created along the cable. Base on the reflection of these waves and by considering of cable length, the fault location can be found. The old and widely used methods similar to the traveling wave method, is the reflectometer method of the time and frequency domain [10, 11], and today, this method is used for laboratory equipment production and measurement, and is theoretically known. From the other new methods, the methods based on wavelet transform can be mentioned. Today, different kinds of wavelet transform in combination with other methods have been used [12-15]. This method is based on the detachment of the fault current and voltage waveforms based on their frequency content at different intervals of time. Then the fault is detected from the variation of these frequency contents by methods based on

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the pattern recognition. Among the new methods to identify the electrical power cables fault, the method based on analyzing signal to noise ratio can be mentioned [16]. In this method, the signal to noise ratio in certain intervals is measured and each time these measurements are compared with previous measurements and in the case of high sudden change, the fault in the phase is detected. In recent years the methods based on the expert systems such as methods based on the fuzzy logic like fuzzy method or fuzzy-neural adaptive inference system. The above mentioned methods have been mostly developed for fault location. This method has showed high accuracy because its rules have been designed based on the "if-else' rules. So it has showed better and more accurate answers compared to many of the classic methods [17-19].

In this paper disclosing the common faults in the underground transmission cable system via the fault detection and fault classification algorithms have been studied. In the proposed method, the artificial neural network has been used as classifier. Also for increasing the performance of neural network to recognize the fault rate, the wavelet transform as an effective input to noise-free the input signal and the bee algorithm to adjust the optimal values of control parameters of neural network has been used. The simulation results in MATLAB software show that the proposed method has good performance in fault detection of faulty phases.

2. Introduction of used tools in fault detection

In this section wavelet transform, classifiers and the optimization algorithm used in the proposed method has been introduced. The MLP neural network with different learning algorithms and the used RBF neural network will be introduced. The different parameters of MLP neural network has been chosen with trial and error. In this network, the neuron and also layer numbers in the hidden layers are determined experimentally and by considering the classification results. The initial weights are determined accidentally and in each program

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run. The RBF neural network has a scattering parameter which determines and controls by bee algorithm. Also to increase the diagnostic performance of neural network, the wavelet transform factors have been used as input.

2.1. Wavelet Transform

The wavelet analysis is a method to analyze a signal that its basis has been built by Joseph Fourier. For lots of signals, low frequency values are the most important parts of the signal, and actually these values, identifies the signal and the high frequency values are the minor changes in the signal. In wavelet analysis, we often discuss about approximation and details. Approximations are the high scale components (low frequency) and details are the low scale components (high frequency) [20]. The signal wavelet analysis and obtaining the details and approximations factors are possible in two ways:

- Single-stage decomposition
- Multi -stage decomposition

In this method the decomposition process can be repeated, so that the approximations one after the other and respectively are decomposed and the signal breaks to the components with less detachment power. This process is called wavelet decomposition tree. Because the decomposition process take places frequently, theoretically, it can be continued to infinity but in reality it can be continued until the specific details of a sample or pixel can be obtained. In practice, we take appropriate steps based on the nature of the signal, or by a suitable criterion [20]. In this study the multi-stage decomposition method has been used according to Fig. 1.

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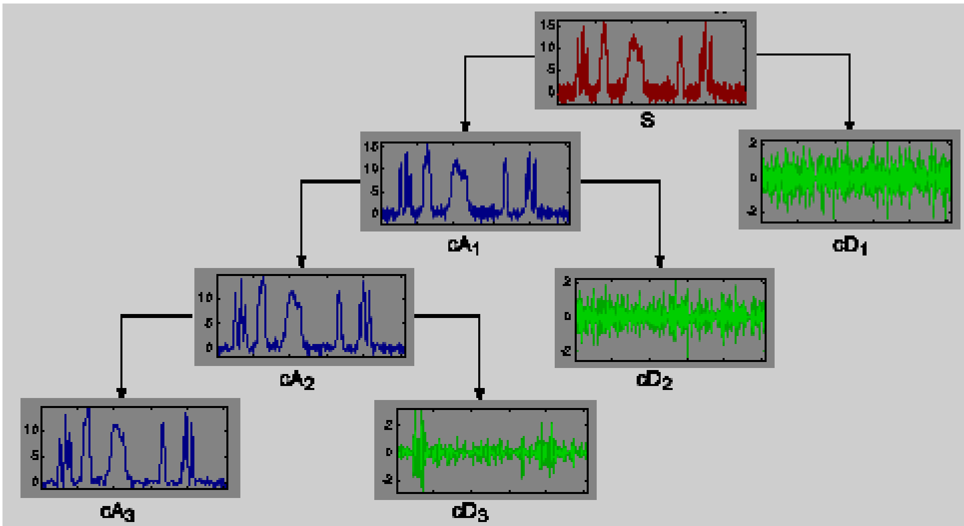

Figure 1: Multi-stage wavelet tree

2.2. MLP neural networks

A MLP neural network consists of an input layer including source nodes, one or some hidden layer including computational nodes (neurons) and one output layer. The number of nodes in input and output layers depends on input and output variables, respectively. The structure of this neural network has been shown in Fig. 2.

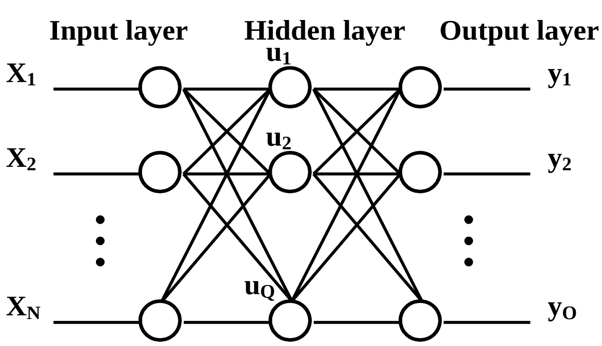

Figure 2: The structure of MLP neural network

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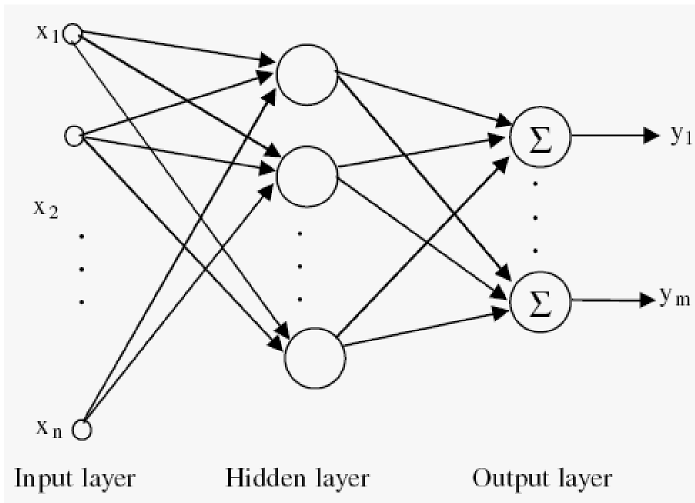

Figure 3: The structure of RBF neural network

The learning algorithm issue is very important for MLP neural network. The Back propagation (BP) learning algorithm is one of the most common algorithms. In this study different kinds of BP algorithm, which has been shown in table 1, has been used.

2.3. RBF Neural Network

The RBF neural networks, in addition to their simple structure and efficiency of their learning, are suitable tools to perform a nonlinear mapping between the input and output vector spaces. The RBF neural network is a full-connected forward structure, and consists of three layers: an input layer, a single layer for nonlinear processing and an output layer [22]. The RBF structure has been shown in Fig. 3.

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Table 1: Nine different learning algorithms for teaching the MLP neural network	
Algorithm	**Acronym**
Resilient	**RP**
Scaled Conjugate Gradient	**SCG**
Polak-Ribiére Conjugate Gradient	**CGP**
Conjugate Gradient with Powell/Beale Restarts	**CGB**
Fletcher-Powell Conjugate Gradient	**CGF**
Broyden, Fletcher, Goldfarb, and Shanno (BFGS) Quasi-Newton	**BFGS**
One Step Secant Quasi-Newton	**OSS**
Levenberg-Marquardt	**LM**
Variable Learning Rate	**GDX**

2.4. Bee Algorithm

The bee algorithm is an optimization algorithm, which inspires from natural exploratory behavior of honey bees to find food, to reach to the optimal solution that was developed firstly in 2005 [23]. In first version of this algorithm, the algorithm perform a kind of local search which has combined with random search and can be used for hybrid optimization, when we want to optimize several variables simultaneously, or functional optimization. Some of this algorithm parameters needs to be initialized such as: The number of watch bees (n), the number of selected places between n visited places (m), the number of the best places between the m selected places (e), the number of the best soldier bees for the best e places (*nep*), the number of soldier bees other places (m-e), the selected places (*nsp*), The initial size of pieces (*ngh*), which include the place and its neighbourhood and stop criterion. The algorithm starts to work with n watch bees, which have been placed randomly in search space. The evaluation of visited places by watch bees is evaluated in second stage. The Pseudo Code of this algorithm is as follows:

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1. Initialize the solution population
2. Evaluate the value of population
3. If the stop criterion is not met, create new population.
4. Select the places for neighbourhood search
5. Selecting soldiers for selected places (more bees for better *e* places) and evaluate their value.
6. Select the most adaptive soldier for each place
7. Force the remaining bees to search randomly, and evaluate their value.
8. The End

3. The Proposed Method and the Simulation Results

In this paper, two methods have been proposed. To evaluate the proposed methods, these methods have been tested on the practical and real data. These data are including 200 samples of three types of fault and normal mode, each pattern includes 50 samples. These patterns are as follows:

a) Normal mode
b) Single phase to ground fault
c) Double phase to ground fault
d) Three phase to ground phase

In Fig. 4 the four signals have been shown. As it can be seen, these four cases are very similar to each others and their experimental separation is very difficult and practically impossible. The 20 percent of data have been used for network teaching and the remaining 80 percent data, for network test. In first method, the MLP neural network has been used as classifier. To reach the best results, the different algorithms for neural network learning have been tested and their results have been compared to each others. Also, to increase the recognition accuracy, the wavelet transform factors have been used as neural network input.

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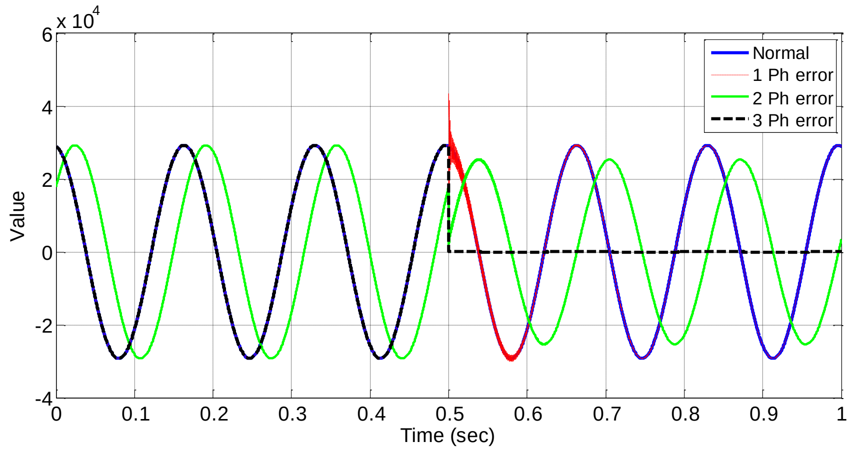

Figure 4: Four case study signal

In second method the RBF neural network has been used to classify. In RBF neural network, the number of radial functions and their distribution has high influence on system performance. For this reason, in addition to use the wavelet transform factors as neural network input, the bee algorithm has been used to find the optimal number of the radial and distribution functions.

3.1. First Method: The Fault Separation by MLP Artificial Neural Network

To evaluate the proposed method, a number of tests have been done, which will be described in the following. The different structures of the MLP neural network have been evaluated to find the optimal solution for fault recognition problem. To evaluate the system performance, different numbers of layers and also different numbers of neurons in hidden layers, have been considered in various tests. The output vector (objective) has been defined with a series of "0" and "1", to show each output class that must be recognized, properly.

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Table 2: The obtained result by original data and different kinds of learning algorithms

Algorithm	Time (second)	Number of iteration	(٪) Recognition Accuracy
RP	**15**	**45**	**95.47**
SCG	**16**	**40**	**94.67**
CGP	**23**	**64**	**94.74**
CGB	**18**	**77**	**95.12**
CGF	**21**	**39**	**95.05**
BFGS	**28**	**23**	**94.87**
OSS	**18**	**38**	**94.69**
LM	**29**	**25**	**94.88**
GDX	**19**	**54**	**94.23**

Table 3: The obtained result by wavelet transform detail factors and different kinds of learning algorithms

Algorithm	Time (second)	Number of iteration	(٪) Recognition Accuracy
RP	**3**	**18**	**99.21**
SCG	**3**	**32**	**99.06**
CGP	**4**	**42**	**98.65**
CGB	**4**	**32**	**98.95**
CGF	**5**	**21**	**99.03**
BFGS	**5**	**20**	**99.13**
OSS	**3**	**22**	**99.15**
LM	**9**	**15**	**98.67**
GDX	**5**	**36**	**98.55**

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As it was mentioned before, the number of neurons in hidden layer has high influence on system performance. For this reason, in this test, the number of neurons of this layer has been chosen after widespread tests. Based on these test and their results, the transfer functions of middle layer have been chosen the "sigmoid tangent" and the output layer has been chosen "linear". In tables 2 and 3 the tests results have been shown. By comparing the tables 2 and 3, it can be seen that using of wavelet transform detail factors as neural network input, has improved the recognition accuracy. The highest accuracy obtained by MLP neural network and the raw data is %95.47, which has obtained by RP learning algorithm. If the wavelet transform detail factors are used as neural network input, the accuracy will be increased to %99.21, so this increase shows the influence of inputs on the performance of the neural network. In figure 5 an 6 the neural network convergence diagram by RP learning algorithm with raw data and with wavelet transform detail factors, respectively has been shown. The pink point shows the best number of learning process iteration. If the network is learned more than this number of iteration, it will be "overfit". In other word, after this number of iteration, the network dominates on the learning data and learns them well, but do not perform well on the test data. When the raw data had been used as input, the neural network had been able to reach to final solution after 44 iterations, whereas by new input (wavelet transform factors) the network could reach to final solution after 16 iterations. To demonstrate the favorable performance of the first proposed method, to separate the introduced faults from each other, the results of the overlap or classify matrix (Confusion Matrix) can be presented. If the fault recognition from each other has been performed with 100 percent accuracy, this matrix must be a diagonal matrix. But if there was a percentage of error in the process of fault recognition and fault separation from each other, this matrix is non-diagonal and has the other non-zero elements. The row of this matrix represents the real classes and the column of it represents decision classes. The matrix numbers represents in a way that when they multiplied by 100, represent the percentage of joints that belong to a certain class and classify in a specific class.

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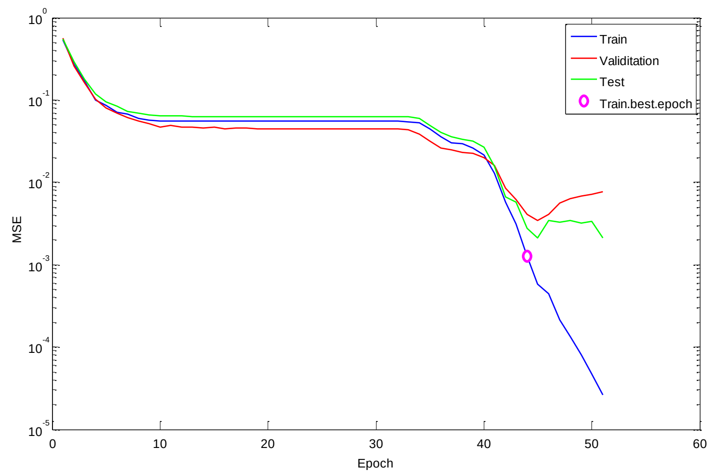

Figure 5: The convergence diagram of the MLP neural network by RP learning algorithm and with raw data

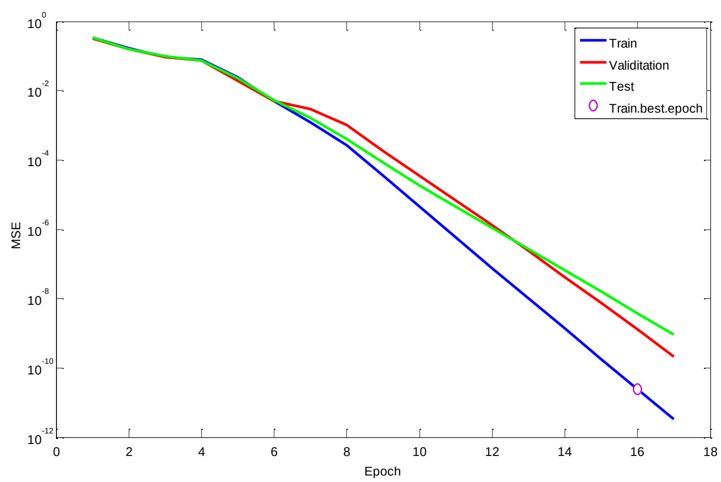

Figure 6: The convergence diagram of the MLP neural network by RP learning algorithm and with wavelet transform input

In tables 4 and 5 the overlap matrix obtained by simulations for fault separation by MLP neural network and by RP learning algorithm with raw data and also with wavelet transform

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detail factors as input, has been shown, respectively. The Fig. 7 shows the used wavelet transform detail factors, typically in 5th level.

Table 4: The overlap matrix for the best obtained result from the MLP neural network trained with RP algorithm and with raw data as input

	Normal	Single phase	Two phase	Three phase
Normal	98	2	0	0
Single phase	1	94	4	1
Two phase	1	2	96	1
Three phase	0	0	3	97

Table 5: The overlap matrix for the best obtained result from the MLP neural network trained with RP algorithm and wavelet transform detail factors as input

	Normal	Single phase	Two phase	Three phase
Normal	99.5	0.5	0	0
Single phase	1	99	0	0
Two phase	0	0	99.5	0.5
Three phase	0	0	0.5	99.5

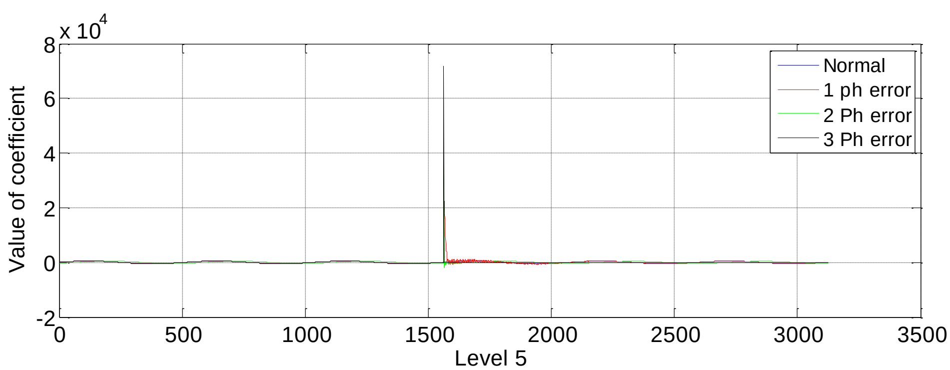

Figure 7: The wavelet detail factors in 5th level

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3.2. The Second Method: The Fault Separation by RBF Artificial Neural Network

As it was mentioned, in RBF neural network, the distribution parameter has high influence on the system performance. For this purpose, in this section, the bee algorithm has been used to find the optimal value of this parameter. In every optimization algorithm, the important issue is the appropriate description of the fitness function. In this method the fault must be minimal. For this reason in first stage, the RBF neural network is made by a radial function and the best value of separation is chosen by the bee algorithm. If the obtained accuracy was not acceptable, one number is added to the number of radial function, and the bee algorithm searches for the optimal value of separation, again. Adding the number of the radial functions will continue to achieve acceptable accuracy. The maximum number of the radial functions equals to the learning data. Adding one to one of radial functions make the network structure smaller, the computations will be reduced, so the system efficiency will be increased. The flowchart of the proposed method has been shown in Fig. 8.

The tables 6 and 7 show the obtained results by the proposed method by means of RBF neural network. As it can be seen in these tables, the results of the proposed method with RBF neural network, optimized with wavelet transform detail factors input, is much better than the other methods. In tables 8 and 9 the overlap matrix obtained by simulation for fault separation by means of RBF neural network and by RP learning algorithm with raw data and with wavelet transform detail factors as input for the optimized case with the bee algorithm has been shown, respectively.

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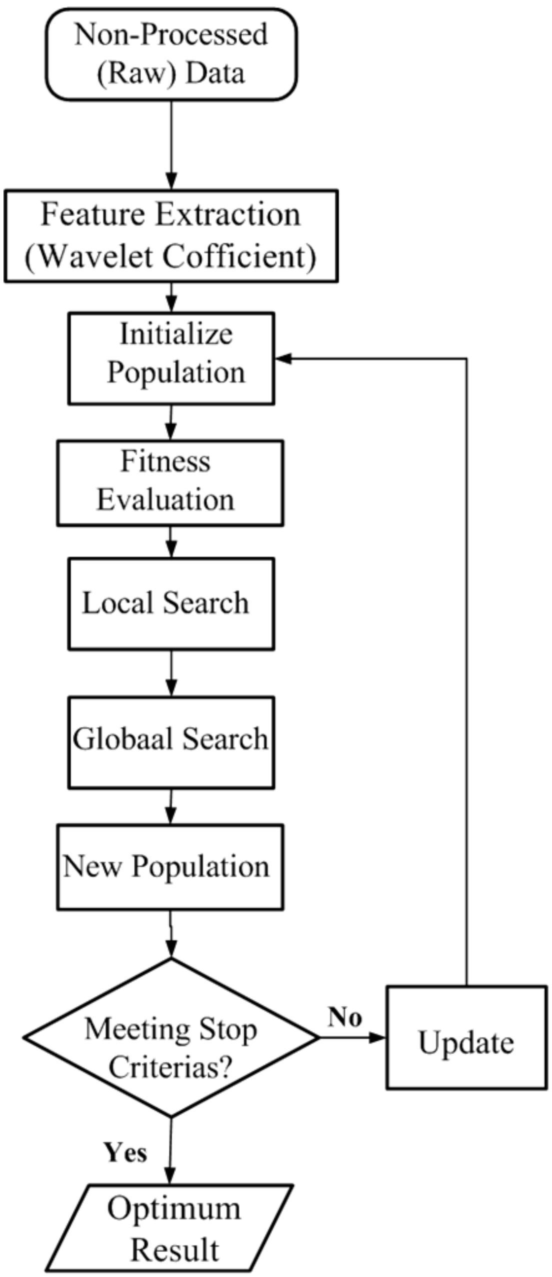

Figure 8: The flowchart of the proposed method

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Table 6: The obtained results by RBF neural network and not optimized for raw data and wavelet transform input

Input	Distribution	Running Time (Second)	(٪) Recognition Accuracy
Raw data	**14**	**10**	**94.78**
wavelet transform detail factors	**9**	**6**	**95.65**

Table 7: The obtained results by RBF neural network optimized for optimal case

Input	Running Time (Second)	(٪) Recognition Accuracy
Raw data	**9**	**97.24**
wavelet transform detail factors	**4**	**99.36**

Table 8: The overlap matrix for the best obtained result of the optimized MLP neural network with the bee algorithm and trained by RP algorithm and with raw data as input

	Normal	Single phase	Double phase	Three phase
Normal	**99.5**	**0.5**	**0**	**0**
Single phase	**2.5**	**97.5**	**0**	**0**
Double phase	**0**	**0**	**99.5**	**0.5**
Three phase	**0**	**0**	**2.5**	**97.5**

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Table 9: The overlap matrix for the best obtained result of the optimized MLP neural network with the bee algorithm and trained by RP algorithm and with wavelet transform detail factor as input

	Normal	**Single phase**	**Double phase**	**Three phase**
Normal	**100**	**0**	**0**	**0**
Single phase	**0**	**99**	**0**	**0**
Double phase	**0**	**0**	**99**	**1**
Three phase	**0**	**0**	**1**	**99**

Conclusion

One of the important issues in the performance study of power cables is monitoring or condition surveillance. Today, by considering the design and production of the power cables in different voltage levels and its favorable capability for energy transmission, and on the other hand, development of intelligent approaches and using them in monitoring systems, the effective and modern monitoring system methods for cable systems has been introduced by researchers. In this paper, a hybrid intelligent system by means of wavelet transform factor and optimized neural network by the bee algorithm for fault recognition has been proposed and studied. Firstly one of the common and widely used neural networks, the Multi Layer Percepton (MLP) neural network has been used for fault recognition with raw data. The simulating results showed that using of raw data as input, makes the computation magnitudes larger and the running time longer. Also for complexity of the problem, the network cannot solve the problem favorably. For this reason, the main data of the wavelet transform has been used as neural network input. The results study showed that choosing the wavelet transform detail factors makes the system accuracy higher. The radial neural network has been used for fault recognition. In the radial neural network, the distribution parameter has high influence on the system performance. For this reason, the bee algorithm has been used for finding the

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optimal value of this parameter. The simulation results showed that by using the optimized radial neural network and wavelet transform detail factor as input, the highest accuracy %99.36 has been obtained, that can almost recognize all kinds of the faults with high accuracy.

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