❏   10

Wavelet energy moment and neural networks based particle swarm optimisation for transmission line protection

Salah Sabry Daiboun Sahel, Mohamed Boudour
Electrical & Industrial Systems Laboratory-LSEI, University of Sciences & Technology Houari Boumediene of Algiers
BP.32 El-Alia, Bab Ezzouar 16111 Algiers, Algeria

Article Info	ABSTRACT
	In this study, a combined approach of discrete wavelet transform analysis and a feed forward neural networks algorithm to detect and classify transmission line faults. The proposed algorithm uses a multi -resolution analysis decoposition of three-phasecurrents only to calculate the wavelet energy moment of detailed coefficients. In comparison with the energy spectrum, the energy moment could reveal the energy distribution features better, which is beneficial when extracting signal features. Theapproach use particle swarm optimization algorithm to train a feed forward neural network. The goal is the enhancement of the convergence rate, learning process and fill up the gap of local minimum point.The purposed scheme consists of two FNNs, one for detecting and another for classifying all the ten types of faults using Matlab/Simulink. The proposed algorithm have been extensively tested on a system 400 kV, 3 phases, 100 km line consideringvarious fault parameter variations.

Corresponding Author:

Salah Sabry Daiboun Sahel,
Electrical & Industrial Systems Laboratory-LSEI,
University of Sciences & Technology Houari Boumediene of Algiers BP.32 El-Alia,
Bab Ezzouar 16111 Algiers, Algeria
Email: salahsabry@yahoo.fr

1. INTRODUCTION

Transmission lines as vital part of power system is subject to constant disturbances created by faults created by natural causes, and sometimes as a result of equipment or operator failure. Transmission line faults have to be confirmed and located quickly and accurately in order to restore power delivery as quickly as possibleand to maintain stability. The fault-generated voltage and current contain abundant fault information, such as time of fault occurrence, fault location, fault direction, and so on. This information varies according to different fault conditions (i.e. loading condition, fault resistance, fault inception instance, etc.). It is important to analyze the fault transient signal and extract the fault features for fast protection, fault type identification, and fault location.

Because of these requirements, a significant amount of research work has been directed to address the problems of an accurate fault detection and classification scheme and regardless of different schemes presented in literature, the advantages of high-frequency based methods are the high accuracy and fast decision making. However, the majority of these methods demand very high measurement sampling rate in the order of tens of kilohertz. But with the fast development of computers and the application of large-scale scientific computing, wavelet analysis as a new branch of mathematics, has been applied to power systems, especially in transient signal analysis. Among the various techniques reported wavelet based techniques are used for detection and classification of faults in power system by researchers. A discrete wavelet transforms analysis (DWTs) in combination with an artificial neural network (ANN) for detecting and classifying fault events in [1]. The DWT acts as an extractor of distinctive features and ANN for classifying fault conditions.

Fault phase selection and fault classifications are carried out by application of particle swarm optimisation (PSO)-based multi-layer perceptron neural network with the help of WTs in [2]. In order to classify faults in underground distribution system DWT in combination with Back-propagation Neural Networks Algorithm (BPNN) are used in [3]. Daubechies4 (db4) is employed as mother wavelet. The maximum values from the first scale at ¼ cycle of three phases and zero sequence of post-fault current signals obtained and have been used as an input for the training process of the BPNN in a decision algorithm. Wavelet-ANN method for classification are also purposed on a HV network in [4]. The features, which are provided as an input to ANN, includes maximum and minimum level 3 and level 4 detailed coefficients of line voltage and energies using Daubechies-3 (db3) as a mother wavelet. The line voltages and phase current signals are recorded for a time of 2cycles.i.e.1 prefault cycle and during fault cycle. To improve the performance of distance relay in transmission system compensated with FACTS a technique was proposed of pre-processing module based on DWT with Daubechies (db4) in combination with ANN and Gaussian Process (GP) for detecting and classifying fault events in [5]. A method for fault classification in 765 kV system was proposed in [6]. DWT analysis with 10 KHz sampling frequency is done by capturing of voltage and current signals by using db4 wavelet up to 7th level, then calculated energy from the detailed coefficient and importing it to ANN for fault classification. Fault detection and classification scheme for transmission line protection using wavelet transform with DB-4 wavelet up to level 3 and linear discriminant analysis (LDA) was purposed in [7]. A combined approach of Wavelet (DB4) and Artificial Neural Network to classify the single line and double line faults for protection of transmission line were presented in [8-9]. Inputs given to the neural are approximate and detailed coefficient of wavelet transform. Different architectures of ANN are tested with the statistical attributes of a wavelet transform of a voltage signal as input features and binary digits as outputs. Fault detection and classification method was also purposed using DWT and ANN, the features used are maximum and minimum detail coefficient of three-phase current signal of d4 and d5 in [10]. The wavelet decomposition for modal current signal, sending end & receiving end modal voltage signal up to 7th level using db4 as mother wavelet. A method for fault classification in series compensated EHV transmission using multi-resolution wavelet transform and ANN purposedin [11].

This paper presents a combined approach of discrete wavelet energy moment and particle swarm optimisation (PSO)-based feed-forward neural network (FNN) for transmission line faults detection and classification. DWT analysis with 10 KHz sampling frequency is done by capturing of current signals by using db5 as mother wavelet up to 6th level, then calculated wavelet energy moment from the detailed coefficient and importing it to ANN for fault detection and classification. The application of back-propagation neural network (BPNN) algorithm have some limitations, such as low learning efficiency, local optimum problems, the need to guess the number of hidden layers, and unstable weights, which are derived from the training patterns. In order to overcome some the limitations, in this paper, FNN trained by PSO (particle swarm optimization) algorithm is used for fault detection and classification by using single-end information of the faulted line. The purposed scheme consists of two FNNs, one for detecting and another for classifying all the ten types of faults using Matlab/Simulink. The proposed algorithm have been extensively tested on a system 400 kV, 3 phases, 100 km line with lumped parameters presentation, considering wide variations in fault location, fault inception angle and fault resistance.

2.　THE PROPOSED FAULT DETECTION AND CLASSIFICATION METHOD
2.1.　Discrete Wavelet Transform
Wavelet transform (WT) has become popular in the field of transient analysis because of its important feature to detect very minute distortion in the fault signals. Similar to Fourier transform (FT), Wavelet transform decomposes a signal into different frequencycomponents present in the signal. But wavelet transform emerges superior to Fourier transform as it divides the frequency band non-uniformly and can realize time–frequency localization for signals [12]. The performance of wavelet transform depends on the selection of an appropriatewavelet function known as "mother wavelet". The mother wavelet is shifted and dilated to get the wavelet coefficients. In Discrete Wavelet Transform (DWT), a time- scale representation of a discrete signal is obtained using digital filtering technique. The signal needed to be analyzed is passed through different filter having different cutoff frequency at different scales. When the fault occurs on transmission line it carries high and low frequency component which frequency signals called details. The signal of the desired component can be extracted via repetitious decomposition. Number of decomposition steps should be decided by comparing the scale of sampling frequency with that of the frequency component of the desired signal. This decomposition process is called Multi-Resolution Analysis (MRA) and was introduced in this context in 1988/89 by Stephane Mallat [13]. The Mallat algorithm consists of series of high-pass and the low-pass filters that decompose the original signal x[n], into approximation a(n) and detail d(n) coefficient, each one corresponding to a frequency bandwidth. The procedure starts with

passing this signal x[n]through a half band digital low-pass filter with impulse response h[n]. For the system taken here, we used 10 kHz as sampling frequencies and Daubechies5 (db5) as mother wavelet. The idea isillustrated in Figure 1 which mathematically is expressed as.

$$y_{high}[k] = \sum_n x[n].H[2k - n] \tag{1}$$
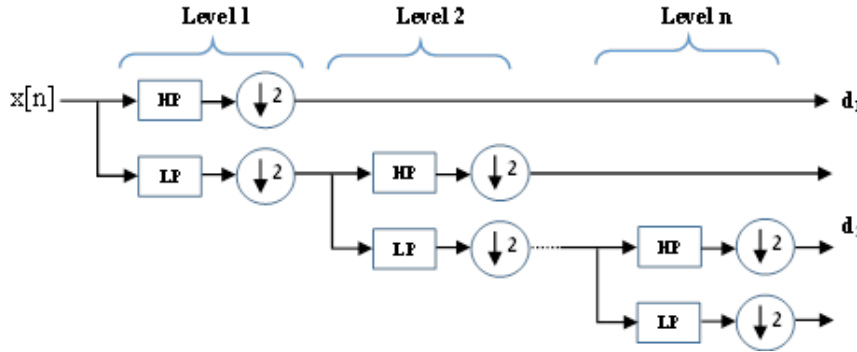
$$y_{low}[k] = \sum_n x[n].L[2k - n] \tag{2}$$

Figure 1. Wavelet transform decomposition of the analysed signal

2.2. Energy moment of Discrete Signal
The total energy of a discrete signal x[n] is given for (3) [14]:

$$E = \sum_{n=-\infty}^{+\infty} x^2[n] \tag{3}$$

In order to better describe the energy at each decomposition frequency band and its distribution characteristics in a time axis, we use the concept of energy moment Mj [15]. By wavelet transform decomposition of the analysed signal, and reconstruct the decomposed signals in a single branch. Then the energy moment Mj of signal Ejk at each frequency band is given by:

$$M_j = \sum_{k=1}^{n} (k.\Delta t) \left| E_j(k.\Delta t) \right|^2 \tag{4}$$

where Δt is the sampling time interval and n is the total number of samples.
The energy moment Mj not only considers the energy amplitude but also describes the energy distribution across time. In comparison with the energy spectrum, the energy moment could reveal the energy distribution features better, which is beneficial when extracting signal features. The wavelet energy moment of each frequency band is affected greatly when the system is under abnormal operating conditions The basic steps to extract the signal features using the wavelet energy moment are as follows:
a.   Step1. Select the proper wavelet base and decomposition levels to decompose the sampled signal by wavelet transform. Let x be the original signal, and let Djk be the detail coefficient at level j and instant k of wavelet decomposition. j=1, 2,.. , J^{jk} , J+1, and J is the largest decomposition level.
b.   Step2. Reconstruct the detail coefficients to obtain the signal component Ejk at each frequency band.
c.   Step3. Calculate the wavelet energy moment Mj of Ejk by (4)
d.   Step4. Construct the feature vectors. Thus, we could construct a feature vector T:

$$T = \left[M_1, M_2, ...M_{J+1}\right] / \left[\sum_{j=1}^{J+1} (M_j^2)\right]^{1/2} \tag{5}$$

2.3.   PSO-BASED Neural Network
2.3.1. Particle swarm optimization algorithm
PSO algorithm based on the swarm intelligent evolution technology was invented by Kennedy and Eberhart that was inspired by the social behavior of animals, such as bird flocking and fish schooling [16]. PSO has been adopted to optimize the complicated problems that are non-linear and non-differentiable. Because of its rapid convergence, simple calculation and easy implementation.
The system initially has a swarm of random solutions. Each potential solution, called a particle, is given a random initial velocity and is flown through the problem space [17]. These particles find the global

best position by competition as well as cooperation among themselves after some iteration. The total number of particles is n, the position of the i-th particle in the searching space is expressed as $X_i = (x_{i1}, x_{i2}, \cdots x_{ik})$; the velocity of the i-th particle in the searching space is represented as $V_i = (v_{i1}, vx_{i2}, \cdots v_{ik})$. The position X_i of i-th particle represents a solution of the problem and velocity V_i of the i-th particle represents its displacement in the searching space. Pbesti is the optimal fitness position that the i-th particle has experienced, and pbesti is the optimal fitness that the i-th particle has experienced. Gbest is the optimal position that all particles have experienced and gbest is the optimal fitness that all particles have experienced. When Fit($\cdot$) is the fitness function for solving the maximum value, the optimal position of each particle is shown in the following equation;

$$Pbest_i(t + 1) = \begin{cases} Pbest_i(t) \, \text{for} \, \text{Fit}(X_i(t + 1)) \leq \text{Fit}(Pbest_i(t)) \\ X_i(t + 1) \, \text{for} \, \text{Fit}(X_i(t + 1)) > \text{Fit}(Pbest_i(t)) \end{cases} \tag{6}$$

To improve the convergence, gbest and Gbest are selected by comparing with the experiences of others. Therefore, the i-th particle is guided to three vectors (Vi, Pbesti, and Gbest). The inertia weight method, as shown in (7) and (8), is applied to update velocity and position of the particles.

$$V_{ij}^{new} = w \cdot V_{ij} + c_1 \cdot rand1 \cdot (Pbest_{ij} - X_{ij}) + c_2 \cdot rand2 \cdot (Gbest_j - X_{ij}) \tag{7}$$

$$X_{ij}^{new} = X_{ij} + V_{ij} \tag{8}$$

where; Pbesti=(Pbesti1,…,Pbestij,…, Pbestik)
　　　Gbest=(Gbest1,…,Gbestj,…, Gbestk)
　　　$w = w_{max} - iter \cdot (w_{max} - w_{min})/iter_{max}$

w_{max} is maximum coefficient of the inertia weight, w_{min} is minimum coefficient of the inertia weight, c_1 and c_2 are the cognitive and social acceleration constants [18], $rand1$ and $rand1$ are uniformly distributed random numbers in the range [0, 1], iter is the current iteration number and $iter_{max}$ is maximum iteration number. In addition, the velocity of the particle is limited to the range [V_{min},V_{ma}x]. Given the PSO method described above, the process of the PSO is shown as the following steps:

a.　Step 1. Generate equivalent n quantity of position and velocity randomly, and record Pbesti, pbesti, gbest, and Gbest;
b.　Step 2. Calculate each fitness value of particles;
c.　Step 3. If stopping criterion is satisfied (e.g., maximum iteration number), the procedure would go to the end; otherwise, proceed to Step 4;
d.　Step 4. Update the Pbesti and Pbesti;
e.　Step 5. Update the gbest and Gbest;
f.　Step 6. Update particles position and velocity by applying (7) and (8), and then go back to Step 2.

2.3.2. PSONN algorithm
In this study, PSO is applied to train a FNN for enhancing the convergence rate and learning process. The basic element of a NN is a neuron. Each neuron is linked with its neighbors with an associated weight that represents information used by the net to solve a problem. The learning process involves finding a set of weights that minimizes the learning error. According to Ref. [19], the position of each particle in a PSONN represents a set of weights for the current iteration. The dimension of each particle is the number of weights associated with the network. The learning error of this network is computed using the MSE (mean squared error) or maximum number of iteration. The particle will move within the weight space attempting to minimize learning error.

The learning process of PSONN is initialized with a group of random particles (step 1), which are assigned random PSO positions (weight and bias). The PSONN is trained using the initial particles position (step 2). Then, the feed-forward NN in PSONN will produce the learning error (particle fitness) based on an initial weight and bias (step 3). The learning error at the current epoch or iteration will be reduced by changing the particles position, which will update the weight and bias of the network.

The "pbest" value (each particle's lowest learning error so far) and "gbest" value (lowest learning error found in entire learning process so far) are applied to the velocity update that refers to (7) to produce a value for position adjustment to the best solutions or targeted learning error (Step 4). The new sets of positions (NN weight and bias) are produced by adding the calculated velocity value to the current position value using the movement equation that refers to (8). Then, the new sets of positions are used to produce new learning errors for the FNN (step 5). This process is repeated until the stopping conditions, either minimum

learning error or maximum number of iteration are met (step 6). The optimization output, which is the solution for the optimization problem, was based on the gbest position value.

2.4. Purposed fault detection and classification procedure

During fault, the magnitude and frequency of the test signal will change significantly as the system changes from normal state to fault. The proposed techniques detect if there is a fault or the transmission line is under normal conditions (0, 1). Furthermore, the algorithm determines the type of fault if it is a single line to ground (SLG) fault, line to line (L–L) fault, double line to ground (DLG) fault or a three line to ground (3LG) fault. Finally, the algorithm selects the phases involved in the fault. The structure of the full-suggested scheme is shown in Figure 2.The pre-processing and processing steps performed by the algorithm consist of generating suitable signals using three phase currents and zero-sequence current samples from CTs to calculate the features that are provided as an input to ANN. The features includes calculated the wavelet energy moment of detailed coefficients at level 6 and using Daubechies-5 (db5) as a mother wavelet. The phase current signals are recorded for a total time of 3 cycle (60ms), first half cycle (10ms) for fault detection, and one cycle for classification of three phases and zero sequence of fault current signals. The simulation data for training the PSONN based detector and PSONN based classifier are generated by using the MATLAB/SIMULINK program to simulate the types of fault as mentioned above.
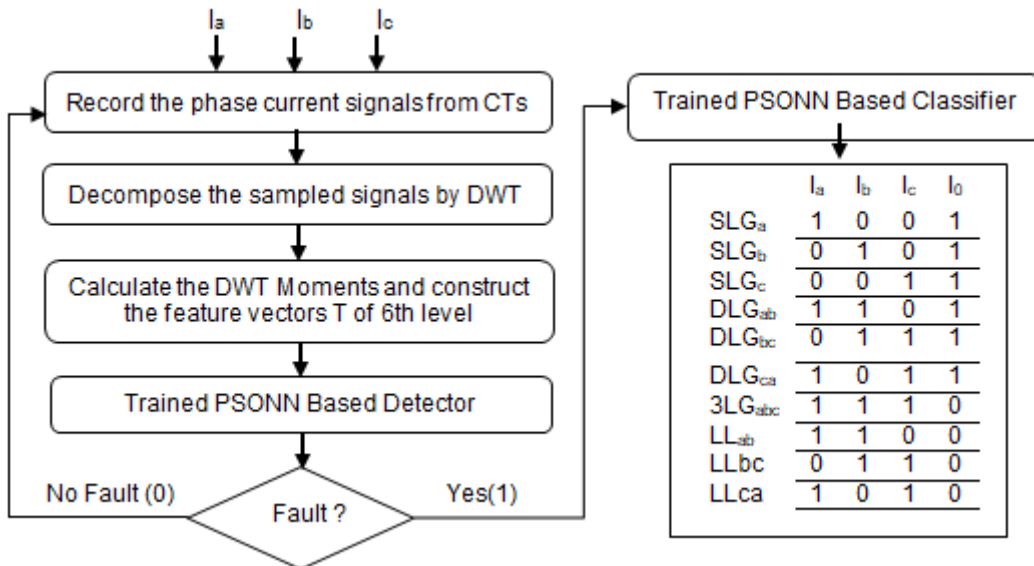

Figure 2. Purposed fault detection and classification

3.   SIMULATIONS AND RESULTS

The single line diagram of the power system network under consideration is shown in Figure 3 the fault detection and classification are accomplished by using samples of three phase currents and zero sequence current for detecting and classifying faults. Zero sequence current is obtained from algebraic sum of the three phases currents. Various fault parameter variations such as fault type, fault location, fault inception angle, and fault resistance are studied. The total number of fault cases simulated for training including variations in fault type: SLG, DLLG, LL, 3LG faults, fault locations, fault inception angles, and fault resistances. Associated parameters for purposed scheme are presented in Table 1.
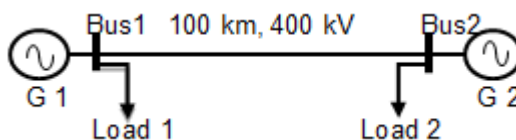

Figure 3. One line diagram of simulated system

Table 1. Associated parameters for purposed scheme

System under study
Sources G1, G2: 400 kV, 50 Hz,1250 MVA and X/R ratio is 10
Load 1:100 kW and 100 kVar , **Load 2:**200 kW
Length of transmission line:100 km
Line Constanst:
R0=0.3864 (Ω/km), L0=4.1264e-3 (mH/km), C0=7.751e-9 (nF/km)
R=0.01273 (Ω/km), L=0.9337 (mH/km), C=12.74e-9 (nF/km)
Generation training patterns
Fault type: SLG (a, b, c), DLG (bc, ca, ab), LL (bc, ca, ab), 3L/3LG (abc),
Fault location (from the relay location at bus 1): 0 to 100km with step of 5km;
Fault resistance: 0 to 50Ω with step of 5Ω
Fault inception angle: 0, 45, 90 deg
Total number of patterns selected: 2541 (for detection), 2310 (for classification) 50% for training dataset and 50% for testing dataset.
Details of Wavelet and associated paremeters
Mother wavelet: Daubechies 5 (db5)
Sampling frequency: 20 kHz
Information analyzed: Detail at level 6
Frequency band of D6: 156 Hz-312 Hz
Number of samples per cycle: 400
Occurrence of fault: 3cycles (60 ms)
Data window length analyzed: half cycle (10ms) for detector and one cycle (20ms) for classifier
PSONN training
Maximum number of iteration: 20000
Number of particles: 25
w_{max}andw_{min} : respectively 0.9 and 0.4

DWT analysis with 20 KHz which gives sampling frequency of 400 samples per cycle is done by capturing of three phase currents and zero sequence current signals by using multilevel decomposition and Daubechies5 (db5) as mother wavelet up to 6th level. Figure 4 shows multilevel decomposition of three-phase faultup to 6th level. For example, the Figure 5 illustrate multilevel decomposition of three-phase fault, then the calculated wavelet energy moments from the detailed coefficient as showing in Figure 6 and importing it to ANN for fault classification.
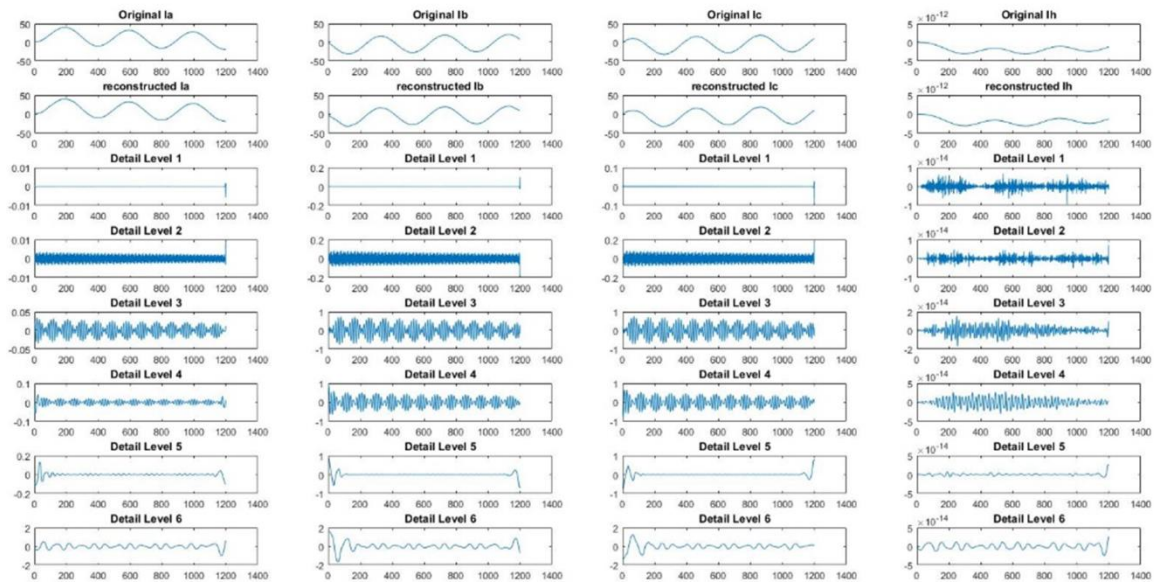

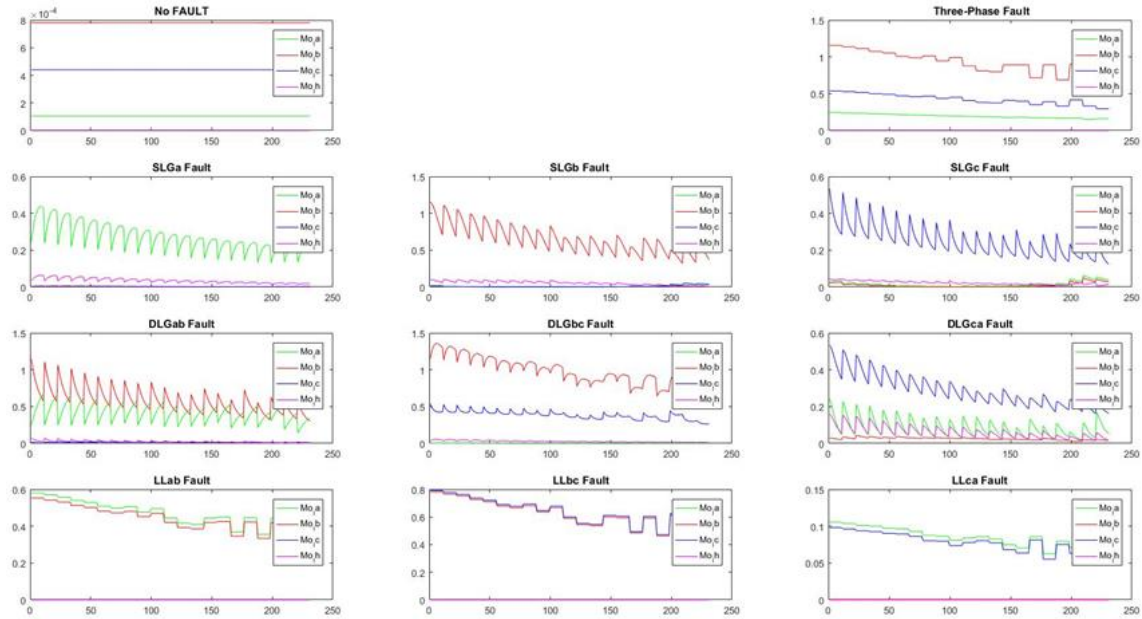Figure 4. Multilevel decomposition of three-phase faultup to 6th level

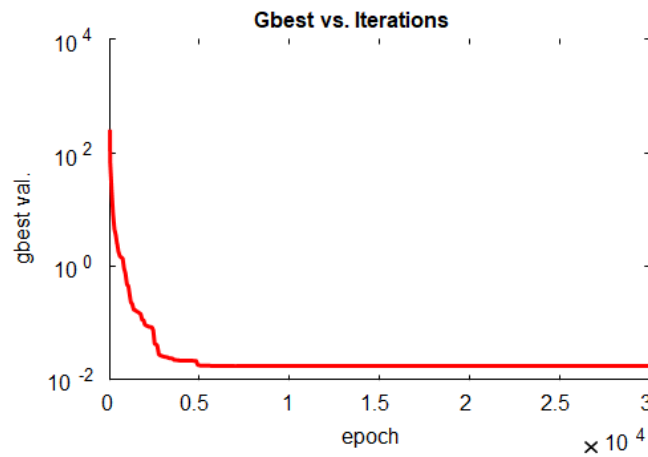Figure 5. Wavelet energy moments from the detailed coefficient of the ten faults

Figure 6. Training process of PSONN based fault detector

Fault detection

The neural network is provided with four inputs during the fault detection process. feature vectors are the calculated wavelet energy moments of detailed coefficients at level 6 of three phases currents and and zero sequence current for a time of 10 ms (1/2 cycle). All ten different types of faults and no fault condition have been considered in developing the data set. The training set consist of total 2541 input and 2541 output samples (2310 for each of the ten faults and 231 for the no fault case), which basically forms a set of four inputs and one output in each input–output pattern. The output of the PSNN is just a yes or a no (1 or 0) depending on whether or not a fault has been detected. After extensive simulations, it has been decided that the desired network has two hidden layer with 4-8-6-1 configuration (4 neurons in the input layer, 2 hidden layers with 8 and 6 neurons in them respectively and 1 neuron in the output layer). Figure6 illustrates the convergence to the optimal solution as minimum fitness against number of epochs of the training process of the neural network.

Figure 7 illustrates PSNN based fault detector responses for all ten faults of the validation/test data set. Fault type, fault location, fault resistance and incipient angle were changed toinvestigate the effects of these factors on the performance of the proposed algorithm. During testing, the outputs are rounded towards

nearest integer (1 or 0). For each case, it can be seen that the PSONNs' outputs converge to the desired values, and are either near to 0 or to 1. The percentages of the overall accuracy is 100% in all fault cases.
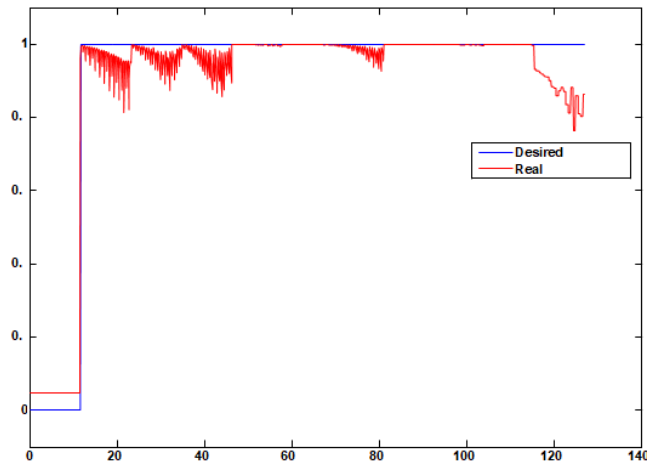

Figure 7. PSNN based fault detector responses

Fault classification

After fault detection module detects whether there is a fault in theline or not. If there is a fault in the line then the faultphases are identified and faults are classified as shown inFigure 3. Fault classification module is designed for each phase and for fault involve or not ground. Output of each phase is '0'when no fault and '1' whenthere is a fault in any of the phases and for fault involvingground. After the fault phases areidentified, fault classification occurs. Considering the same assumption of fault detection module,the neural network is provided with four inputs during the process. The inputs feature vectors that are the calculated wavelet energy moments of detailed coefficients at level 6 of three phases currents and and zero sequence current for a time of 20 ms during fault cycle. The training set consist of total 2310 input and 2310 output samples, which basically forms a set of four inputs and four output in each input–output pattern. Figure 8 shows the convergence to the optimal solution as minimum fitness against number of epochs of the training process of the neural network classifier with 4-16-8-4 configuration (4 neurons in the input layer, 16-8 hidden layers with and 4 neuron in the output layer). The classification percentages of the overall accuracy accuracy is 98,79%. As an example Table 2 shows some of results with conditions system which was not presented to the PSONN during the training process.
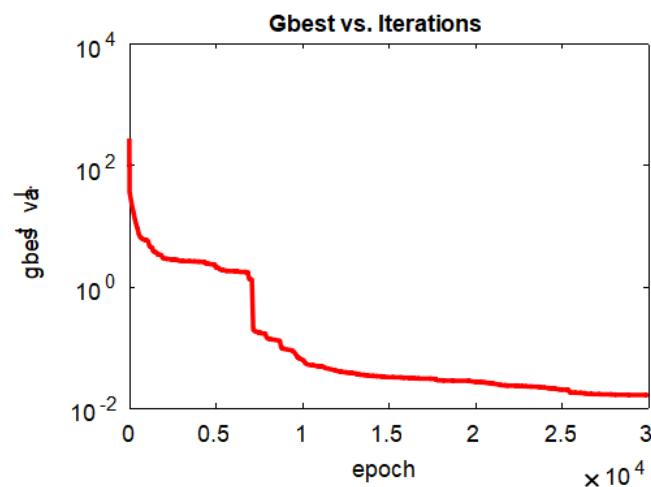

Figure 8. Training process of PSONN based fault classifier

Table 2. PSONN based fault classifier response

Fault Type	Desired Output	FL=4m	FL=55m	FL=95m
		Fault resistance 4Ω, Inception angle 0°, Fault location (FL) km		
SLG-a	1	0.9803	0.9675	0.9561
	0	-0.0452	-0.0017	0.0446
	0	-0.0450	-0.0071	0.0669
SLG-b	1	0.9641	0.9780	0.9828
	0	0.1998	-0.0642	0.1177
	1	0.9971	0.9875	0.9957
SLG-c	0	-0.0920	0.0419	0.1083
	1	0.9951	0.9880	0.9930
	0	0.1543	0.1828	0.2396
DLGab	0	-0.0534	-0.0301	-0.0273
	1	0.9939	0.9928	0.9915
	1	0.9861	0.9896	0.9899
	1	0.8455	0.8940	0.8976
DLG-bc	1	1	1	1
	0	0.0996	0.0462	-0.0143
	1	0.9992	0.9992	0.9993
	0	-0.0725	0.06159	0.1612
DLG-ca	1	0.9990	0.9989	0.9988
	1	0.9847	0.9847	0.9836
	1	0.8160	0.7733	0.7667
	1	0.9481	0.8899	0.828
LL-ab	0	0.0387	-0.0080	0.0424
	1	0.9922	0.9929	0.9899
	1	0.8313	0.8972	0.9635
	1	0.9997	0.9997	0.9994
LL-bc	1	0.9947	0.9901	0.9663
	0	-0.0237	-0.0056	0.0079
	0	-0.0027	0.0345	0.1620
	0	-0.0423	-0.0047	0.0239
LL-ca	1	0.9738	0.9686	0.9537
	1	0.9921	0.9928	0.9936
	0	0.0429	-0.0029	0.0707
	1	0.999	0.9990	0.9862
3L/3LG	0	0.0107	0.0004	0.0031
	1	0.9357	0.9232	0.9039
	0	-0.0189	-0.0134	0.0343
	1	0.9818	0.9703	0.9686
	1	0.9997	0.9995	0.9995
	1	0.9714	0.9754	0.9757
	0	0.0461	0.0165	0.0265

Comparison with other schemes

The performance of PSONN-based fault detector and classifier for all types of faults is verified. Proposed method is compared with other as shown in Table 3. The advantages of proposed method are the use single-end information, only two mudules one for detection and the second for classification, PSO algrithm to train FNN to overcome limitations of back-propagation algorithm in addition the use of wavelet energy moment is very sensitive when the system is under fault conditions comparing with the use of detailed energy coefficients. It is observed that the proposed method provides a very good detection and classification since the % success in detection is 100% and in classification is 99.65% success including all type of operating conditions, the errors in the classification and location ANN were under 1%.

Table 3. Comparison with other schemes

References	Aims of scheme and used Tools	Description technique	Over all accuracy
Upendar et al. [20]	-Fault classification -DWT and PSO-ANN	Current signals are being decomposed into nine levels using the MRA algorithm with DB1. The input contains 512 (12.77 kHz) samples. During fault condition, the detailed coefficients of 7th level with the frequency band of 99–199 Hz have higher magnitudes owing to the presence of second and third-order harmonic content in the line currents.	99.91 % for classification
Noha Mahmoud Bastawy et al. [5]	-Fault Detection and Classification -DWT, ANN and GP	In other to detecting and classifying a fault for transmission line compensated with FACTS, two preprocessing module purposed DWT in combination with ANN and DWT in combination with Gaussian Process (GP)	Detection: 100% for both DWT-ANN and GP Classification: 96.2% for DWT-ANN 90% for GP
Yadav A and Swetapadma A [7]	-Fault Detection and Classification -DWT and LDA	Technique approximate DWT coefficients with DB4 wavelet up to level 3 of three phase currents and wavelet reconstruction process are used as inputs to linear discriminant analysis (LDA) based fault detector. Three phase currents and zero sequence currents as input to LDA based fault classifier. Fault detection and classification are carried out in separate modules 10 modules for detection and 4 modules to identify and classify the faults up to 99% of line within one cycle time.	100% for both detection and classification
Gowrishankar et al. [10]	-Fault Detection and Classification -DWT and ANN	The fault signals decomposed up to 5th detail level using DWT with DB6 to obtain feature extraction. The feature extracted are maximum and minimum detail coefficient value of three phase current signal at level 4 and level 5. Features taken as input to a feed-forward BP-ANN structure using scaled conjugate gradient algorithm.	90.60 % for classification
Purva Sharma et al. [9]	- Fault Detection and Classification -DWT and ANN	The DWT with DB4 of system voltages are calculated. Mean, standard deviation, norm, maximum and minimum values of detailed energy coefficients are taken as potential input features for construction of the classification engine with 5 cycle transition time.	Not mentioned
Purposed Method	-Fault Detection and Classification -DWT, WEM and PSO-ANN	DWT analysis is used with DB5 and sampling frequency of 10 KHz to obtain detailed coefficients at level 6 and to calculate wavelet energy moment (WEM). The algorithm use half cycle for fault detection, and one cycle for classification of three phases and zero sequence of fault current signals. The purposed scheme consists of two modules, one for detection and another for classification. Proposed scheme can detect and classify faults up to 99% of line.	100% for detection and 99.65% for classification

4. CONCLUSION

Methodologies for detection and classification of transmission line faults based on FNN trained with PSO algorithm have been presented tested and compared. The scheme consists of two FNNs, one for detecting and another for classifying all the ten types of faults. The features provided as an input to ANN includes calculated the wavelet energy moment of detailed coefficients at sixth level and using DB5 as a mother wavelet. The use of energy moment reveal the energy distribution features better when extracting signal features under fault conditions. The proposed algorithm have been extensively tested on a system 400 kV, 100 km. In this study, faults detected and classified correctly. The overall accuracy obtained is very high in both detection function and classification function. Furthermore, it is observed that the detection and classification results are highly accurate, even with wide variation in system conditions.

REFERENCES

[1] F. Martin and J. A. Aguado, "Wavelet-based ANN approach for transmission line protection," in *IEEE Transactions on Power Delivery*, vol. 18, no. 4, pp. 1572-1574, Oct. 2003.

[2] Shaaban S.A, Hiyama T. *Transmission Line Faults Classification Using Wavelet Transform*. Proceedings of the 14th International Middle East Power Systems Conference (MEPCON'10), Cairo University, Egypt. December 2010:19-21.

[3] Kaitwanidvilai S, Pothisarn C, Jettanasen C, Chiradeja, Ngaopitakkul A. *Discrete Wavelet Transform and Back-propagation Neural Networks Algorithm for Fault Classification in Underground Cable*. Proceedings of the international Multionference of Engineers and Computer Scientists. Hong Kong. March. 2011; Vol II :16-18.

[4] Beg M. A, Bundhe N. G, Paraskar S. R, Pratibha. Classification of Faults on 400 KV Transmission Line. *International Journal of Science, Spirituality, Business and Technology*. February 2013; 1(2): 2277—7261.

[5]   Bastawy N. M, Talaat H. E, Ibrahim A. M. Fault detection and classification based on DWT and modern approaches for T. L compensated with FACTS. *American Journal of Electrical Power and Energy Systems*. 2013; 2(6): 149-155.

[6]   Raikwar V. T, Kankale R. S, Jadhav S. EHV Transmission Line Fault Classification. *International Journal of Industrial Electronics and Electrical Engineering*. July-2014; 2(7): 2347-6982.

[7]   Yadav A, Swetapadma A. A novel transmission line relaying scheme for faultdetection and classification using wavelet transformand linear discriminant analysis. *Ain Shams Engineering Journal*. 2015 ; 6:199–209.

[8]   SharmaP, Saini D, Saxena A, Fault Detection and Classification in Transmission Line UsingWavelet Transform and ANN. *Bulletin of Electrical Engineering and Informatics (BEEI)*. September 2016; 5(3): 284-295.

[9]   Purva Sharma P, Deepak Saini, Akash Saxena, Fault Detection and Classification in Transmission Line using Wavelet Transform and ANN. *Bulletin of Electrical Engineering and Informatics (BEEI)*. December 2016; 5(4): 456-465.

[10]   Gowrishankar M, Nagaveni P, BalakrishnanP. Transmission Line Fault Detection and Classification Using Discrete Wavelet Transform and Artificial Neural Network. *Middle-East Journal of Scientific Research*. 2016; 24 (4): 1112-1121.

[11]   P. D. Raval and A. S. Pandya, "Improved fault classification in series compensated EHV transmission line using Wavelet transform and Artificial Neural Network," *2016 IEEE 1st International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES)*, Delhi, 2016, pp. 1-5.

[12]   Chul Hwan Kim and Raj Aggarwal, "Wavelet transforms in power systems. I. General introduction to the wavelet transforms," in *Power Engineering Journal*, vol. 14, no. 2, pp. 81-87, April 2000.

[13]   S. G. Mallat, "A theory for multiresolution signal decomposition: the wavelet representation," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 11, no. 7, pp. 674-693, July 1989.

[14]   Corinthios M. Signals, Systems, Transforms, and Digital Signal Processing with MATLAB. Boca Raton : CRC Press, Taylor & Francis Group. 2009.

[15]   He Z. Wavelet analysis and transient signal processing applications for power systems. Singapore; Hoboken, NJ: John Wiley & Sons. 2016.

[16]   J. Kennedy and R. Eberhart, "Particle swarm optimization," *Proceedings of ICNN'95-International Conference on Neural Networks*, Perth, WA, Australia, 1995, pp. 1942-1948 vol.4.

[17]   Nedjah N, Mourelle L.M.Swarm Intelligent Systems: Foundations,Perspectives and Applications. Verlag Berlin Heidelberg Springer. 2006, 26:3-25.

[18]   Lee C.Y, Shen Y.X, Cheng J.C, Li Y.Y, Chang C.W. *Neural Networks and Particle Swarm Optimization based MPPT for Small Wind Power Generator*. World Academy of Science, Engineering and Technology Conference. Dec 2009 ; 60:17.

[19]   Daiboun Sahel S. S, Boudour M. Fault Location in Transmission Lines Using BP Neural Network Trained with PSO Algorithm. *Journal of Energy and Power Engineering*. 2013;7: 603-611.

[20]   J. Upendar, C. P. Gupta, G. K. Singh and G. Ramakrishna, "PSO and ANN-based fault classification for protective relaying," in *IET Generation, Transmission & Distribution*, vol. 4, no. 10, pp. 1197-1212, October 2010.