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Detection and classification of faults on 220 KV transmission line using wavelet transform and neural network

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Abstract

This paper presents a discrete wavelet transform and neural network approach to fault detection and classification in transmission lines. The detection and classification are carried out by using energy of the detail coefficients of the phase signals, used as input to neural network to classify the faults on transmission lines. Neural network performs well when faced with different fault conditions and system parameters.

Keywords: Fault detection, fault classification, wavelet transform, neural networks.

1. Introduction

Along with other electrical components, the transmission line suffers from the unexpected failures due to various faults. Protecting of transmission lines is one of the important tasks to safeguard electric power systems. For safe operation of EHVAC transmission line systems, the protection system needs to be able to detect, classify, locate accurately and clear the fault as fast as possible to maintain stability in the network. The protective systems are required to prevent the propagation of these faults. The occurrence of any transmission line faults gives rise to transient condition. Fourier transform technique is used for detecting the transmission line faults. Fourier transform gives information about all frequencies that are presented in the signal but does not give any information about the time at which these frequencies were presented. Wavelet transform has the advantage of fast response and increased accuracy as compared to conventional techniques. The wavelet transformation is a tool which helps the signal to be analyzed in time as well as frequency domain effectively. It uses short windows at high frequencies, long windows at low frequencies. Using multi resolution analysis a particular band of frequencies present in the signal can be analyzed. The detection of fault is carried out by the analysis of the wavelets coefficients energy related to phase currents.

The proposed algorithm consists of time-frequency analysis of fault generated transients using Wavelet transform, followed by pattern recognition using artificial neural network. The wavelet transform has the ability to detect the faults, and its time localization property is very good. The neural networks have the ability to learn, generalize and parallel processing has made their applications for many systems ideal. The use of neural network as pattern classifiers is among their most common and powerful applications. The MATLAB/ SIMULINK is used to generate the fault signals and verify the correctness of the algorithm. Wavelet toolbox and Neural Network toolbox are used from the MATLAB7.10 version. The proposed scheme is insensitive to variation of different parameters such as fault type, fault resistance. ANN based techniques have been used in power system protection and encouraging results are obtained [1], [2], [3]. Neural networks are used for different applications as classification, pattern recognition. In classification, the objective is to assign the input patterns to one of the different classes.

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2. Discrete Wavelet Transform

Discrete Wavelet Transform is found to be useful in analyzing transient phenomenon such as that associated with faults on the transmission lines. The fault signals are generally non stationary signals, any change may spread all over the frequency axis. Under this condition the Fourier Transform techniques are less efficient in tracking the signal. S.T.F.T (Short Time Fourier Transform) uses a fixed support window to localize sharp transitions for non-stationary signals. The practical power system fault signal contains fundamental as well as other frequencies. The wavelet transform technique is well suited to wide band signals that may not be periodic and may contain both sinusoidal and non sinusoidal components .The wavelet transform has the ability to focus on short time intervals for high frequency components and long time intervals for low frequency components. Multi-Resolution Analysis (MRA) is one of the tools of Discrete Wavelet Transform (D.W.T), which decomposes original, typically non-stationary signal into low frequency signals called approximations and high frequency signals called details, with different levels or scales of resolution. It decomposes signal into different scales and resolutions. The use of detail coefficients for fault detection is discussed in this paper. Detail coefficients contain information about the fault, which is required for fault detection.

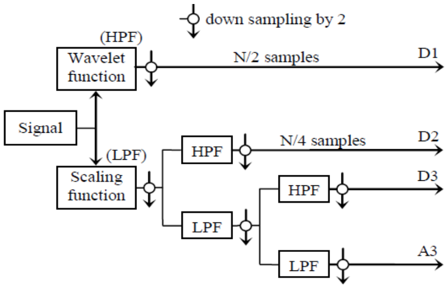

Fig. 1. Wavelet filter bank

It uses filters with different cut off frequencies to analyze a signal at different resolutions. The signal is passed through a series of high-pass filters, also known as wavelet functions, to analyze the high frequencies and it is passed through a series of low-pass filters, also known as scaling functions, to analyze the low frequencies. In the first decomposition, signal is decomposed into D1 and A1, the frequency band of D1 and A1 is $fs/4$– $fs/2$, and 0 - $fs/4$ respectively where the sampling frequency is fs. In the second decomposition step the A1 is decomposed to give A2 and D2. The frequency band of D2 detail level 2 components is $fs/8$– $fs/4$, and A2 approximation level 2 is 0–$fs/8$. The signal of desired frequency component can be obtained from repetitive decompositions as shown by Fig. 1. The mother wavelet determines the filters used to analyze signals. In this paper Db4 (Daubechies 4) wavelet was chosen because of its success in detecting faults [4], [5].

3. Artificial Neural Networks

Artificial neural networks (ANN's) are inspired by biological nervous systems and they were first introduced as early as 1960 [8]. A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. Artificial Neural Networks simulate the natural systems behaviour by means of the interconnection of basic processing units called neurons. Neurons are highly related with each other by means of links. The neurons can receive external signals or signals coming from other neurons affected by a factor called 'weight'. The output of the neuron is the result of applying a specific function, known as a 'transfer function', to the sum of its inputs, plus a threshold value called 'bias'. With these general characteristics it is able to develop different network structures. ANNs have a high degree of robustness and ability to learn. ANNs are prepared to work with incomplete and unforeseen input data. Basic processing model of ANN has 1) neuron, 2) synaptic weights, 3) summing junction, and 4) activation function.

ANN's have the ability to learn from examples. Once the network is trained, it is able to properly resolve the different situations that are different from those presented in the learning process. The weights of the network are adjusted automatically to get a particular target output for specific input. The neural networks can have several layers. Each neuron in one layer has direct connections with all other neurons in the next layer. There can also be hidden layers. By inserting hidden layers, increasing its size and number, the non-linear model of the system is developed. The multilayered feed forward network has the ability of handling complex and nonlinear input-output relationship with hidden layers. In this method, errors are propagated backwards; the idea of back- propagation algorithm is to reduce errors until the ANN learns the training data. The training begins with the random weights and the goal is to adjust them so that the error will be minimal. The multilayered feed forward network has been chosen to process the prepared input data obtained from the W.T.

ANNs are selected depending upon:

1) ANN architecture
2) Transfer function of each neuron
3) Initial weights and biases.
4) Learning rule.

4. Transmission Line Model

In Fig. 2, model of 220kv, 200km transmission line from P to Q is chosen. Generator of 500MW is connected at one end and 4 loads are connected at 13.8kv and 220kv. Various faults are simulated on that line by varying various parameters. Ratings of power system model are shown in Table 1. As shown in Fig. 2 a transmission line model is prepared in MATLAB7.10.

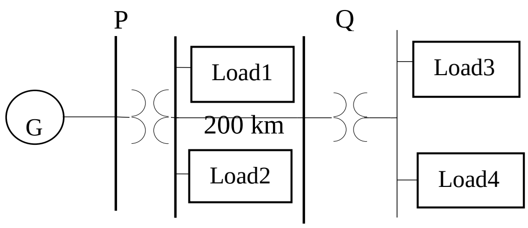

Fig. 2. Transmission Line Single Line Model.

Table 1. Model parameters

1	Generator	500MVA, 13.8kv, 50Hz, synchronous generator pu model
2	Transformer1	13.8kv/220kV, 500MVA.
3	Transfomer2	220kv/13.8kV, 500MVA.
4	Load1	50MW, 220kV, 50MW, 1Mvar, RL load.
5	Load2	50MW, 220kV, 50MW, 1MVar, RL load
6	Load3	13.8kV, 40MW, RL load
7	Load4	13.8kV, 40MW, RL load
8	Transmission line	Length=200km.

The transmission line positive and zero sequence parameters are R1=0.10809Ω/km, R0=0.2188Ω/km, L_1=0.00092 H/km, L_0=0.0032 H/km, C_1=1.25×10^{-8} f/Km, C_0=7.85×10^{-9} f/km. The distributed parameter model of transmission line is considered for analysis. The current signals of three phases and neutral are sampled at sampling frequency of 20 kHz. Different faults as single line to ground, double line to ground, line to line, 3 lines to ground are simulated on transmission line at various system conditions.

5. Design of Fault detection and Classification

The design process of proposed fault detection and classification approach is as follows:

1) Creating of the power system model, data acquisition of current and voltage signals.

2) Changing the system parameters and, acquiring current and voltage signals.

3) Application of D.W.T on the current signals and calculating detail coefficients energy.

4) Selection of suitable ANN topology for given application.

5) Training of ANN and validation of the trained ANN using test patterns to check its correctness and generalization.

Combination of different fault conditions are to be considered and training patterns are required to be generated by simulating different kinds of faults on the power system. The fault resistance, fault location, and fault type are changed to generate different training patterns.

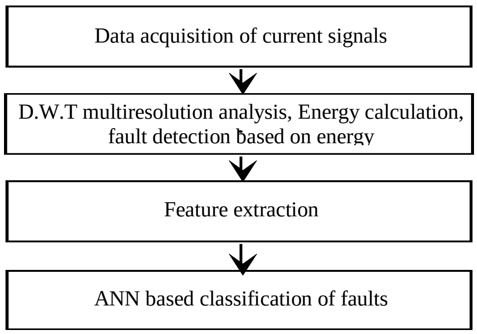

Fig.3. Process of fault detection and classification.

6. Fault Detection

The signals taken from the scope are filtered, sampled at 20 kHz sampling frequency. Then DWT is applied up to level 5, and detail coefficients and approximate coefficients are calculated and detail coefficients energy is calculated. Therefore, for sampling frequency of 20 kHz, the detail level 1 coefficients are in the frequency range of 5 kHz-10 kHz, detail coefficients at level 2 are in the frequency range of 2.5 kHz-5 kHz, the detail coefficients at level 3 are in the frequency range of 1.25 kHz-2.5 kHz, the detail coefficients at level 4 are in the frequency range of 0.625kHz-1.25kHz, and detail coefficients at level 5 are in the range of 0.3125 kHz-0.625 kHz. Then, we come to know that detail level 5 contains highest amount of energy than the level 4.A moving data window of one cycle (400 samples) is taken and decomposition is done and energy of the details coefficients at level 5 is obtained for each data window. As the fault signals contain the high amount of harmonic components, the energy of the signal increases at the occurrence of fault as shown in Fig. 4

Here, for detecting the fault, difference of energies between two adjacent windows has been considered. The energy of detail coefficients for a window is given by Eq. (1),

$$E_d = \sum_{i=1}^{N} D_1^2 \left(i \right) \tag{1}$$

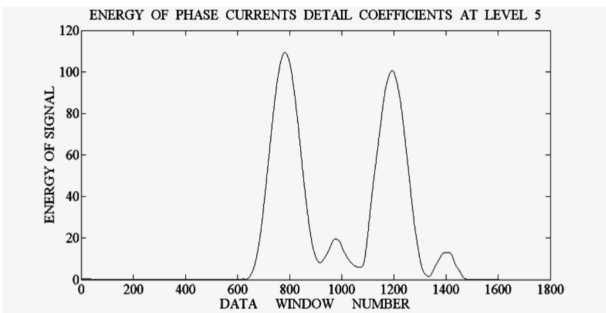

Fig. 4. Energy of the detail level 5 vs. window number.

where, k is the window number, l is the level of the DWT, N is the length of Detail coefficients at level l. For accurately detecting the presence of faults, the difference between the two consecutive energies of the moving windows is calculated by (2) and shown in Fig. 5.

$$F.D(K) = F.D.(K\text{-}1)+[Ed\,(k) \,\text{-}\, Ed\;(K\text{-}400) \quad (2)$$

In this sampling frequency of 20 kHz gives 400 samples for each cycle of 20ms. Here, moving window slides taking only1 new sample at each move and keeping 399 previous samples. So one cycle corresponds to nearly 400 data samples.

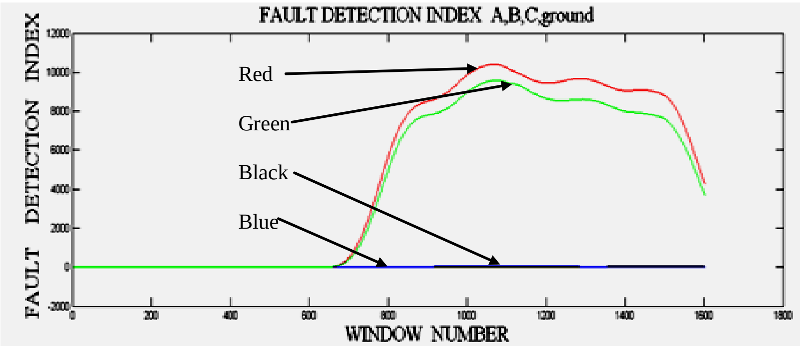

Fig. 5. F.D index for single line to ground fault vs. window number.

The fault is presented on R-phase and ground (G) for the present case. Red colour shows the R phase, green colour shows the ground (G) phase, black colour represents the Y phase and blue colour shows the B phase.The Fault Detection value is compared with threshold value for consecutive 20 data windows, and then decision is made whether fault is permanent or temporary.

By using these Fault Detection values the faults can be accurately detected [7]. For different phases different threshold values are set and the fault detection is achieved. The transient energy is presented mainly during fault inception and clearing. The high frequency content energy is smaller than the low frequency content energy of the current signals.

Table 2. Target outputs

Fault Type	A	B	C	G
AG	1	0	0	1
BG	0	1	0	1
CG	0	0	1	1
AB	1	1	0	0
BC	0	1	1	0
CA	1	0	1	0
ABG	1	1	0	1
BCG	0	1	1	1
CAG	1	0	1	1
ABC	1	1	1	0

7. Neural Network Based Fault Classification

All different faults are simulated for different conditions and training patterns are generated from the energy values of the detail coefficients. The 4 input neurons and 4 output neurons are selected. The two hidden layers are selected. Feed forward multilayer back propagation neural network is selected. The average values of energies of current signals, half cycle after the occurrence of fault are given as input to the neural network, along with the three lines energies, zero sequence current energy is also given as fourth input to the neural network. Three outputs show the statuses of the three phases, if fault is presented it is shown by the presence of '1', otherwise with presence of '0'. Similarly fourth output indicates the ground fault. If ground is involved in the fault will be indicated by the presence of '1', otherwise it is presented by ‘0’. This is shown in Table 2. Generation of different training patter ns is done as shown in Table 3.

Table 3. Training patterns

Type of fault	LG, LLG, LL, LLL.
Location of fault (%) from busbar P.	20,30,40,50,60,70,80
Fault resistance	5,10,15,20 Ω.

Feature information is acquired by the network through a learning process and interconnection synaptic weights are used to store the knowledge. And, then the neural network can generalize generalize, and can give response to any untrained data. For training neural network different fault conditions are simulated, features are extracted and network is trained. At 7 different locations on the transmission line fault is created, at 20, 30, 40, 50, 60, 70, 80% of the transmission line length from the sending end, 4 different values of fault resistances can be used and total 10 different faults are created, and this gives 7*4*10=280 cases for training neural network. Once the network is trained with given training parameters, the network can be simulated for any input and target values and performance measures can be found.

The different training algorithms are presented to train the neural network; they use the gradient of the performance function to determine how to adjust the weights to minimize a performance function. The gradient is determined using back propagation technique, which involves performing computations backwards through the network. A variation of back propagation algorithm called Levenberg-Marquardt (LM) algorithm was used for neural network training, since it is one of the fastest methods for training moderate-sized feed forward neural networks.
LM algorithm to weight update is given by (3),

$$X_{K+1} = X_k - [J^T J + \mu I]^{-1} * J^T * e \tag{3}$$

where J is Jacobean matrix that contains first derivatives of the network error with respect to the weights and biases, e is a vector of network errors. J^T J is an approximation of the Hessian Matrix, $J^T e$ is the gradient and μ is the scalar affecting performance function. LM algorithm based method for training neural network is much faster than the other methods. Fig. 6 shows the multilayered feed forward neural network (M.F.N.N.)

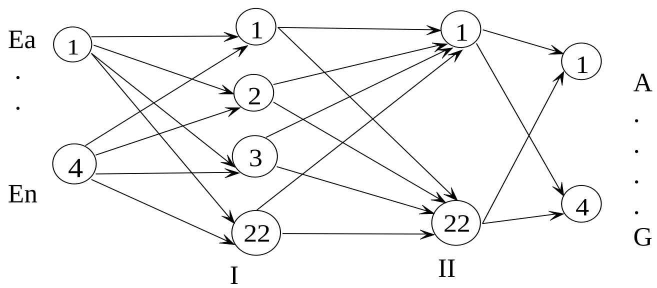

Fig. 6. Multilayer feed forward network for fault classification.

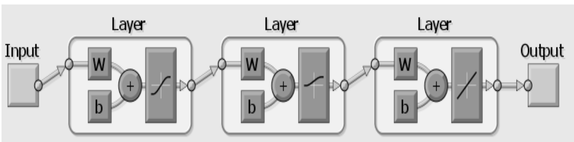

Fig. 7. 4-22-22-4 ‘Tansig’, ‘Logsig’, ‘Purelin’ configuration.

Network with 2 hidden layers worked out to be better than the 1 hidden layer network.4-22-22-4 configuration give better results than the 4-22-4, 4-10-4 configurations. Activation functions used for the hidden layers I, II and output layer are ‘tansig’, ‘logsig’ and ‘purelin’ respectively. The Fig. 7 shows the neural network.

The data used for training data division is done randomly; training function used is LM algorithm. Performance function used is Mean least square error method. The performance goal chosen is 10^{-6}. Fig.8 shows the performance curve. For network configurations 4-22-4 and 4-10-4, we cannot distinguish between the faults with ground without ground.

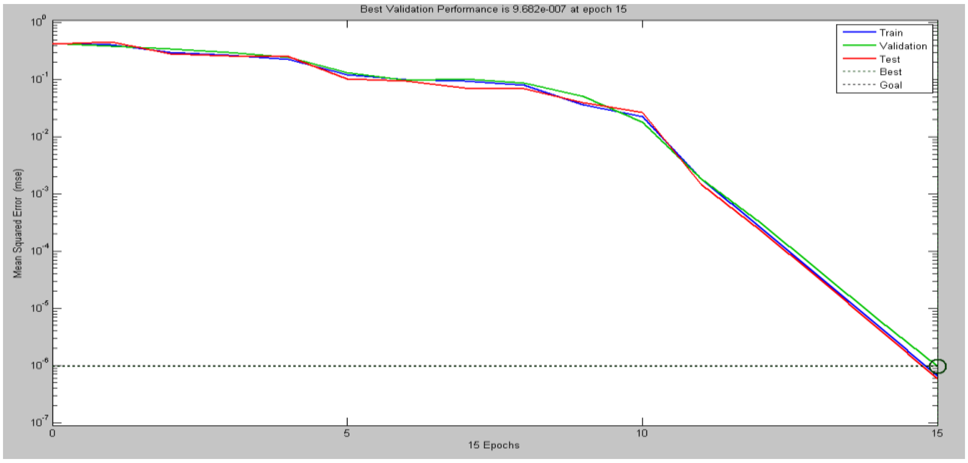

Fig. 8. Performance curve.

8. Test Results

A validation data set consisting of different fault types was generated using the transmission line model shown in Fig. 2. The validation test patterns were different than they were used for the training of the neural network .For different faults on the model system, fault type; fault location and fault resistance values are changed to investigate the effects of these factors on the performance of the proposed algorithm. Test results are as shown in Table 4. These results show the accuracy of neural network for varying fault location values and varying fault resistance value.

Table 4. Testing results

Fault type	Fault location from P (%)	Fault Resistance (Ω)	Output of neurons A	B	C	G
AG	30%	10	1.0001	2×10^{-3}	4×10^{-3}	1.00
BCG	50%	15	0	1.00	0.9989	1.00
CAG	50%	10	1	0	1.00	0.998
CG	50%	10	1×10^{-3}	0.000	1.00	1.00
ABC	30%	10	1.00	1.00	0.999	0.00
ACG	70%	5	0.9996	-3×10^{-4}	0.997	1.000
AB	70%	5	1.018	1.0847	0.1587	0.052

Table 5. Comparison of transfer functions

Transfer Functions for hidden layers	Tansig-tansig	Logsig-logsig	Tansig-logsig
No. neurons in hidden layers	22-22	22-22	22-22
Performance error of test results	2.9×10^{-7}	5.5×10^{-7}	5.39×10^{-8}

The output layer activation function used is ‘Purelin’, because of its success in the classification of faults correctly. The tansig and logsig transfer functions did not show a good classification capability. The output layer transfer function is fixed at ‘Purelin’ and the hidden layer transfer function was changed.

If the transfer functions of the hidden layers I and II are chosen as 1) Tansig-Tansig. 2) Logsig-Logsig. 3) Tansig-Logsig, the Table 5 test result shows that the accuracy obtained with the Tansig-Logsig type of neural network is more and it is having good generalization capability. The classification results for almost all types of faults are satisfactory.

9. Conclusion

In this paper accurate fault detection and fault classification technique are discussed. This technique depends upon the current signals. The features are extracted from the current signals by using wavelet transform. The feature vector is then given as input to the neural network. The capabilities of neural network in pattern classification were utilized. Simulation studies were performed and the performance of the scheme with different system parameters and conditions was investigated. The test result shows that the accuracy obtained with the “tansig-logsig” transfer function for hidden layers I and II is satisfactory. Though the paper deals with fault classification only it can be extended to other power system protection problems, such as finding fault location.

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