

FAULT LOCALIZATION ON THE TRANSMISSION LINES BY WAVELET TECHNIQUE COMBINED RADIAL BASIS FUNCTION NEURAL NETWORK

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ABSTRACT

The rapid growth of the electricity system in the of a country's economic development has led to an increase in the number of power transmission lines operating at different voltage levels and the total length of power transmission lines. Thus, Faults on the transmission line are unavoidable. In this paper, Wavelet transforms for the recognition and localization of short circuits faults on the power transmission lines. In that, the voltage waves and current waves on the lines are simulated by Simulink - Matlab. The Wavelet transform is used with the RBF Neural network to find out where the short circuit faults occurred. The proposed method is applied for a power system which is a power transmission lines, one load and one generator. The results are achieved and demonstrated the potential for on-line identification capabilities in Vietnam Power System. Third-level DWT with mother wavelet db4 is utilized to calculate detailed discrete wavelet energies of fault current, the values of these features are fed to the RBF neural network to estimate fault location on an overhead power line. The algorithm is fast as only half cycle. The accuracy of fault localization is very high at different locations on the transmission line.

Keywords: Power system fault; Multi-resolution analysis; Radius bias function Neural Network (RBFNN); Fault location; Power transmission line; Discrete Wavelet transform.

1. INTRODUCTION

A transmission line is one of the important elements of an electric power system. Since 1945, electric power systems have been extremely important because the steep increase in population of most countries has caused a huge increase in electric energy demand [1, 2]. As a result, power transmission lines have been rapidly developed in number and length. One important factor of an electrical power transmission system is to continuously deliver electrical power to consumers.

A problem related to electric power systems is faults occurrence in power transmission lines which is an unfavorable and inevitable problem. Short-circuit faults are the worst types of the faults occurring in power transmission lines. Short circuit faults have many harmful effects on the electrical

distribution systems and devices. Some harmful effects are: shortening the life of the electrical devices, increasing power losses and extra heat produced by cables, wires, insulators and transformers [1, 2, 3]. When a short-circuit fault occurs in a transmission line, a power outage is the result which is carried out by protection relays, and as a result, there is an interrupt in delivering electrical power to consumers.

Thus, utilizing some methods or using some devices having capabilities to determine faults location quickly and accurately are necessary. During recent years, applications of artificial neural network (ANN) in power systems such as stability and transient response analysis have attracted many attentions [4,5]. As an application, fault analysis in power transmission systems using ANN has been the subject of some researches [6]. Based on

a radial basis function (RBF) neural network with orthogonal-least-square (OLS) learning procedure, a simple fault classification method was reported in [6]. The method can identify various patterns of associated voltages and currents but it does not have the capability of fault location, and furthermore, some faults cannot be classified because the method cannot identify all possible pat-terns related to different faults. The RBF neural network was also compared with the back-propagation (BP) neural network and it was shown that the RBF neural network can classify faults better than BP neural network. Based on discrete wavelet transform (DWT) in combination with ANN, fault detection and a fault recognition method were reported in [2]. DWT was used to extract different features of input signals (voltages and currents) and ANN was also used to classify faults. The technique is absolutely theoretical and fault location is impossible. A method based on S-transform (ST) and support vector machines (SVMs) for classification.

2. A NOVEL METHOD FOR POWER SYSTEM FAULT RECOGNITION

2.1 Wavelet transform technique

This is an identification fault problem in power systems, which is found out characteristics of power current or voltage signals. A Wavelet transform decomposes these signals into different levels (time and frequency) for identification of specific characteristics. Figure 1 shows a wavelet technique, which decomposes a signal into three levels.

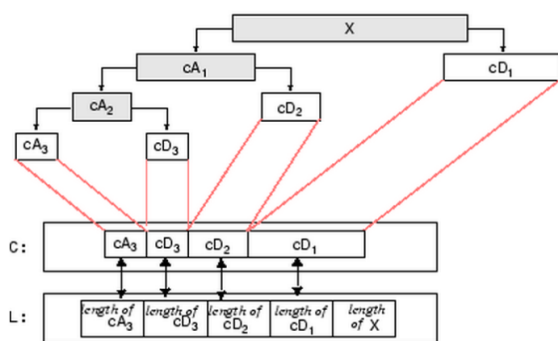


Figure 1. Wavelet decomposition in three levels

At each level, Wavelet detailed coefficients are calculated as following:

$$f_{c_0 rms} = \sqrt{\frac{\|f_{c_0}(t)\|_2^2}{L_{f(t)}}} = \sqrt{\frac{\sum_k d_j(k)^2}{2^{J-j} * L_{d_j}}} \quad (1)$$

L_{dj} : number of Wavelet coefficients,

J : J detailed level,

j : decomposition at j level,

Thus, there are vectors rms_{signal} which compose wavelet coefficients as:

$$rms_{signal} = [f_{c_0 rms} | f_{d_0 rms} | f_{d_1 rms} | \dots | f_{d_{j-1} rms}] \quad (2)$$

The study choose three-level, wavelet Dabuchies 4 (DB4) as mother wavelet to decompose three-level. Wavelet coefficients are calculated in (1) included a3, d3, d2, d1 for a signal. There are seven signals (three voltages and four currents), thus $4 \times 7 = 28$ coefficients are calculated on a vector for event recognition. Generally, a signal is calculated four components in a vector in (3)

$$V_x = [V_{xrms_a3} \ V_{xrms_d3} \ V_{xrms_d2} \ V_{xrms_d1}]^T \quad (3)$$

2.2 Identification algorithm

For recognition and analyzing power system events (normal or fault events) and classification events are shown on Figure 2, thus it is necessary to measure a signal continuously by a sliding window. This window width can be changed for any problem and methods. This study is chosen sliding window achieved 34 samples of signal per cycle.

For recognition a fault, there are 28 features of a power system state can be calculated in (3), thus RBF neural is chosen to classification. And for localization a fault, nearest rules are applied, these rules find the nearest distance of a state vector compared sample vectors to locate a fault. To locate a fault, nearest neighbourhood rules are used to find the nearest distance of a vector to samples for short circuit location.

2.3 Radial Bias Function Neural Network

The radial basis function neural network (RBFNN) has a feed-forward structure consisting of three layers, an input layer, a nonlinear hidden layer and a linear output layer, as shown in Figure 3. Vectors are fed to the network via input layer, which communicates to one or more hidden layer where the actual processing is done.

The hidden layer consist of a set of radial basis function calculates the Euclidean distance between the cente and the input vector, and then, the result is passed to the radial basis function. RBFNN performs a nonlinear mapping from input layer to hidden layer and then the linear mapping from hidden to an output layer.

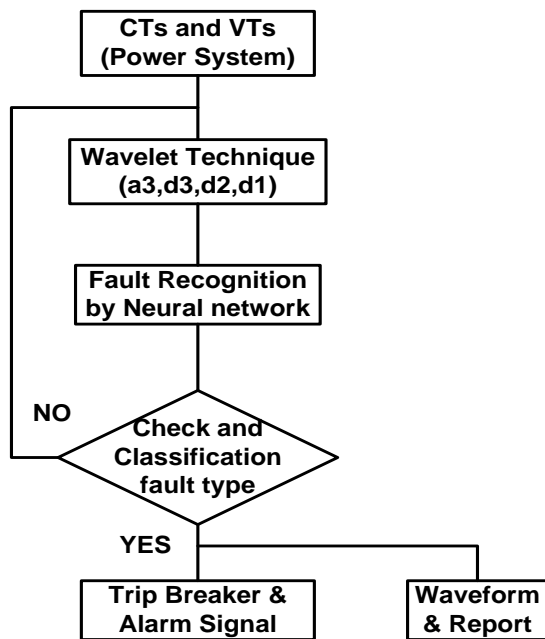


Figure 2. Algorithm for Identification and Classification Faults.

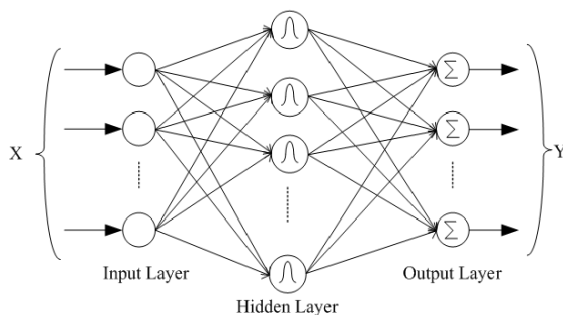


Figure 3. Architecture of Radian basis function neural network

For an input x , the output of the network can be represented as:

$$d_i = w_{oi} + \sum_{j=1}^h \omega_{ji} * \Phi(\|x - c_j\|, \beta_j) \quad (4)$$

Where $i=1, \dots, m$ and $j = 1, \dots, h$, w_{oi} is the biasing term, h is the number of hidden node and the i th output node, c_j is the center of the j th hidden node, β_j is the real constant known as spread factor, and $\Phi(\cdot)$ is the activation function represented in (5) for the j th hidden unit.

$$\begin{aligned} \Phi(z_j, \beta_j) &= \exp(-z_j^2 / \beta_j^2) * z_j \\ &= \|x - c_j\| \end{aligned} \quad (5)$$

In the present work, the normalized current energies of eight DWT frequency bands for each phase are fed to RBFNN for fault location. Thus, the input layer of this RBFNN has 28 inputs and the output layer has one output, i.e., fault location as shown in Fig. 3. One of the important features of this neural network is that it creates neurons in the hidden layer one by one until the error goal is achieved, leading to fast convergence of selection of neurons.

2.4 Overhead Power line and Fault Location

In the present work, a 220 kV, three-phase, 50 Hz power transmission network fed one side is simulated using MATLAB software and the single-line diagram of the power system is shown in Fig. 4. A three-phase balanced load rating of 380 MVA, 0.8 lagging power factor at bus TBD 2 of the transmission line. Faults have been initiated at nine locations for training. The fault signal are recorded at bus TBD 1 for time duration of $50\mu s$ with a sampling frequency of 20 kHz. Current waveforms are shown in Fig. 5.

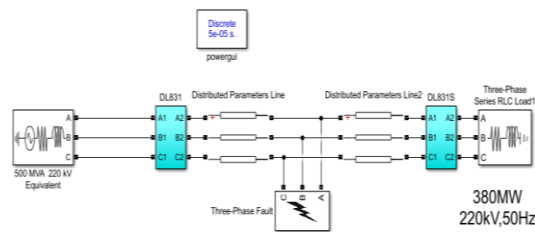


Figure 4. Single-line diagram of the transmission system in MATLAB Simulink.

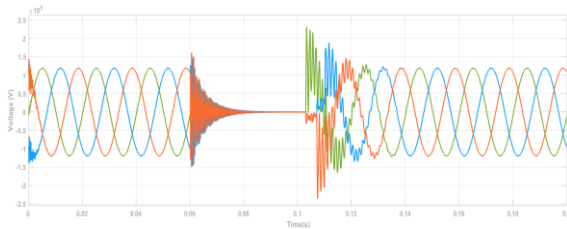


Figure 5. Voltage waveform for three phase fault at 43 km

2.5 Feature Extraction and Fault Localization

The DWT up to third-level decomposition with mother wavelet DB4 has been used for feature extraction of fault currents recorded at two sides. Energy at each detailed level of DWT are calculated, and these are used as fault feature for localization of faults on the transmission line. The extracted features are fed to RBF neural network design in MATLAB for localization of fault on the transmission line. The efficacy of the proposed algorithm has been tested for different locations on the overhead line section. To obtain uniform error for all fault location, the error of fault location is calculated with respect to total length of line as given in (6) and in Table 1. Networks were trained in the Intel core i7 machine with 8G RAM. The RBF neural network was developed for each type of mother Wavelet. Following parameters were used during the training of each RBF. They were trained until the sum square error reached 0.0001 and training time of each was less than 1 minutes in Fig. 6.

$$E\% = \frac{\text{Estimated location} - \text{Actual location}}{\text{Total length of transmission line}} * 100 \quad (6)$$

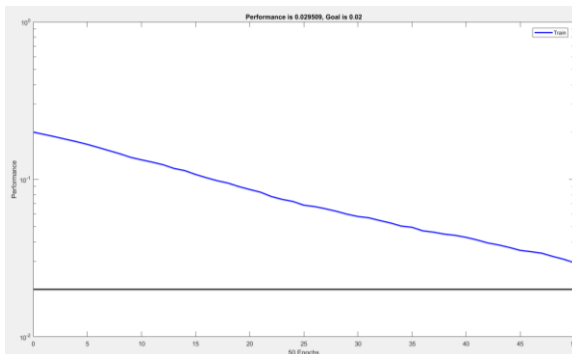


Figure 6. RBF network response for training data

Table 1. Recognition results

Actual fault location (km)	Fault with $R_f=20\Omega$	
	Estimated fault location (km)	E%
15	14.9659	-0.0243
22	21.9921	-0.0056
36	36.0202	0.0145
43	43.0055	0.0039
53	52.9858	-0.0101
67	67.0057	0.0041
76	76.0304	0.0217
87	87.0254	0.0181
92	91.9673	-0.0234

3. CONCLUSION

This paper proposes a fault localization method using radial basis function neural network and wavelet technique for power transmission lines with sampling frequency 20 kHz. Discrete Wavelet transform up to the third level with mother wavelet db4 is applied for feature extraction of the fault current are used as features and fed to Radial basis function neural network for fault localization. The proposed algorithm performs with a high degree of accuracy irrespective of fault resistance and fault types. The major advantage of this algorithm is that this method is fast and independent of fault section for locating fault on the power transmission lines.

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