



Power System Fault Detection and Classification Using Wavelet Transform and Artificial Neural Networks

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Abstract. Power system fault detection has been an important area of study for power distribution networks. The power transmission systems often operate in the kV range with significant current flowing through the lines. A single fault, even lasting for a fraction of a second, can cause huge losses and manufacturing downtime for industrial applications. In this research, we develop an approach to detect, classify, and localize different types of phase-to-ground and phase-to-phase faults in three-phase power transmission systems based on discrete wavelet transform (DWT) and artificial neural networks (ANN). The multi-resolution property of wavelet transform provides a suitable tool to analyze the irregular transient changes in voltage or current signals in the network when fault occurs. An artificial neural network is employed to discriminate the types of fault based on features extracted by DWT. Computer simulation results show that this method can effectively identify various faults in a typical three-phase transmission line in power grid.

Keywords: Power systems · Fault detection · Fault classification · Wavelet transform · Artificial neural networks

1 Introduction

In today's society, electricity is a necessity for our daily lives. From large industrial companies to small households, energy is consumed and always needed to be readily available. A major issue that power companies face is the power transmission discontinuity due to various faults along transmission lines. It is known that the power transmission systems often operate at high voltage (in kV range) for lesser resistive losses over long distance; thus when fault occurs, excessively high current flows through the power network which may cause severe damages to equipment and devices ([1–3]). A single fault, even when lasting only for a fraction of a second, may affect potentially millions of customers on the grid and result in huge losses and manufacturing downtime in industry. These power quality events (PQEs) can be caused by natural disasters, equipment failures, or human errors. For example, a line-to-ground fault may be caused by a fallen tree limb that makes contact with one transmission phase line and the ground. If an object, such as a bird or other animal, makes a contact with two transmission phase lines may result in a short current of these two phases called a line-to-line fault.

The conventional approach to discover and identify faults in power networks is to manually analyze the system. However, this method is usually time-consuming and not very efficient. In recent years, there have been some developments in the applications of computational intelligent models and algorithms for fault detection and diagnosis. In [4], support vector machine (SVM) is employed to detect and classify four different types of faults in a distributed power network. The output of SVM is binary; thus four SVMs are used in the system and each SVM is trained to detect and classify fault for a particular phase. In [5], transformer disturbances in power networks are discussed. Two artificial neural networks (ANN) are connected in cascade form; one for fault detection and one for classification. Once the disturbance is detected by the first neural network, the algorithm enables the second ANN to discriminate different types of faults appropriately. Reference [6] considers the application of a probabilistic neural network (PNN) with discrete wavelet transform (DWT). The details of dataset and simulation results are not given. In [7], DWT and neural networks are combined to detect three different faults for a typical three-phase inverter used in power systems. The inputs to neural network are the normalized approximate coefficients of level 1, 2, and 3 from wavelet transform. The performance of ANN is tested on a limited dataset (12 tests total), with satisfactory results.

This paper focuses on the development of a hybrid approach to detect, classify, and localize different types of phase-to-ground and phase-to-phase faults in three-phase power transmission systems based on discrete wavelet transform and artificial neural networks. The multi-resolution property of wavelet transform provides a suitable tool to extract and analyze the transient changes in voltage or current signals when a network fault occurs. Note this “irregular” change in time domain also results in the change of signal power distribution in frequency domain. In this research, instead of using DWT coefficients directly as proposed in literature, the power of the subband signal (decomposed by DWT) is used as the feature vector. An artificial neural network is then employed to discriminate various types of faults in the network. Seven different cases are considered, namely, no fault, phase A line-to-ground fault, phase B line-to-ground fault, phase C line-to-ground fault, phase A and B line-to-line fault, phase B and C line-to-line fault, and phase A and C line-to-line fault. Computer simulation results show that this method can effectively identify various faults in a typical three-phase transmission line in power grid.

This paper is organized as follows. Section 2 provides the background information on discrete wavelet transform (DWT), artificial neural networks (ANN), as well as the hybrid approach based on DWT and ANN. Section 3 discusses the computer simulation results. Section 4 concludes the paper and gives direction for future work.

2 The Hybrid Approach for Power System Fault Identification

In this section, the background information on discrete wavelet transform and artificial neural networks is introduced first; then the hybrid approach for power grid fault detection based on DWT and ANN is discussed.

For a three-phase power grid, there are two different types of faults, i.e. the symmetric fault and the asymmetric fault. About 5% of power transmission line faults are symmetric (or balanced) faults, which affect each of the three phases equally ([1–3]). Typical symmetrical faults include line to line to line (L-L-L) and line to line to line to ground (L-L-L-G). Asymmetric faults (or unbalanced faults), which do not affect each of the three phases equally, are more common in power systems. Asymmetric faults include line-to-line, line-to-ground, as well as double line-to-ground faults. In this research, we consider six different types of asymmetric faults, i.e., phase A line-to-ground fault, phase B line-to-ground fault, phase C line-to-ground fault, phase A and B line-to-line fault, phase B and C line-to-line fault, and phase A and C line-to-line fault.

Wavelet transform is a powerful mathematical tool for signal processing. It decomposes signals into multiple frequency bands with different resolutions, and is especially suitable to analyze non-stationary signals or to detect irregular transient changes in signals. The continuous wavelet transform of a signal $f(t)$ can be written as:

$$T(\tau, s) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} f(t) \psi^* \left(\frac{t - \tau}{s} \right) dt \quad (1)$$

where $\psi(\cdot)$ is called the “mother wavelet” and $\psi^*(\cdot)$ represents its complex conjugate; s is the scaling factor and τ is the shifting factor. In computer simulations, discrete wavelet transform is performed by selecting

$$s = 2^a, \quad \tau = 2^b \quad (2)$$

where a and b are positive integers.

The wavelet transform can be considered as passing a signal through a set of low-pass (LP) and high-pass filters (HP). Through this process, a signal can be decomposed into various levels. At each level, it contains a set of detail coefficients (D) and approximation coefficients (A). In this research, we use DWT to extract features from the voltage or current signals in the power network. Instead of using DWT coefficients directly as proposed in literature, the power of the subband signal (decomposed by DWT) is used as the feature vector. Daubechies (db4) wavelet is employed for decomposition to level 4; then the power of the subband signal is calculated using detail coefficients of level 4:

$$E_s = \sum_{i=1}^{L_m} (D_i)^2 \quad (3)$$

where D_i is the i^{th} detail coefficient of the decomposition level m which contains totally L_m detail coefficients.

After feature extraction, a neural network model is proposed to classify different types of faults, with the subband signal power obtained from wavelet transform as its inputs. The weights of the neural network are initialized randomly, and then updated with the Levenberg-Marquardt algorithm [8]:

$$W(k + 1) = W(k) + \eta(J_a^T J_a + \mu I)^{-1} J_a^T e \tag{4}$$

where J_a is the first order derivative of the error function with respect to the neural network weight (also called the Jacobian matrix); e is the output error (i.e., the difference between the neural network outputs and the desired outputs. In this application, it represents the classification error); μ and η are learning parameters; and k is the index of iterations.

A typical multi-layer feedforward neural network has an input layer, an output layer, and one or more hidden layer(s). The wavelet transform is performed on three voltage or line current signals, one for each phase (i.e., phase A, B, and C); thus the neural network classifier has three inputs. In this research, by trial and error, we choose the neural network with one hidden layer and ten hidden neurons for the simulation in Sect. 3. The output of neural network represents the type of each fault, or no fault. Therefore, the neural network classifier can have either a single output, or three outputs with the fault type ID binary encoded for seven different cases. Initial training and test results show that the single output neural network classifier performs slightly better than the binary encoded outputs. As a result, in Sect. 3, we choose the neural network with a single output. The overall system diagram is shown in Fig. 1.

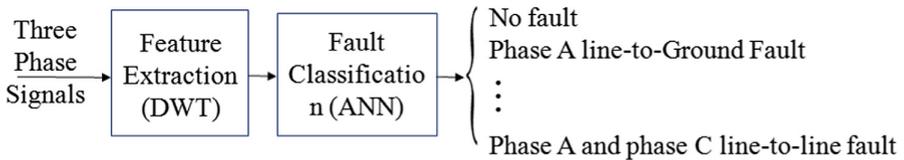


Fig. 1. The power system fault detection and classification using DWT and ANN

3 Simulation Results

A typical configuration of a power grid consists of three major modules, i.e. generation, transmission, and distribution. Figure 2 illustrates the Matlab Simulink model of such a network. In this section, the performance of the proposed approach based on DWT and ANN is tested by computer simulations.

In Fig. 2, the three-phase transmission line between the 50 Hz power generator site and the load is divided into two series-connected portions by the fault location in network, where the first portion shows the connection between the source and fault location; the second portion illustrates the connection between the fault location and the load. The resistance, capacitance, and inductance per unit length for the positive- and zero-sequence of the transmission lines are summarized in Table 1. These values of parameters are chosen to match with the parameters of the power source. Note the transmission line is continually transposed; i.e., the positive and negative sequences are equal. Also, a small non-zero ground resistor should be included. In this simulation, it is chosen to be 0.001 Ω. All of these values of parameters can be varied upon one’s choice.

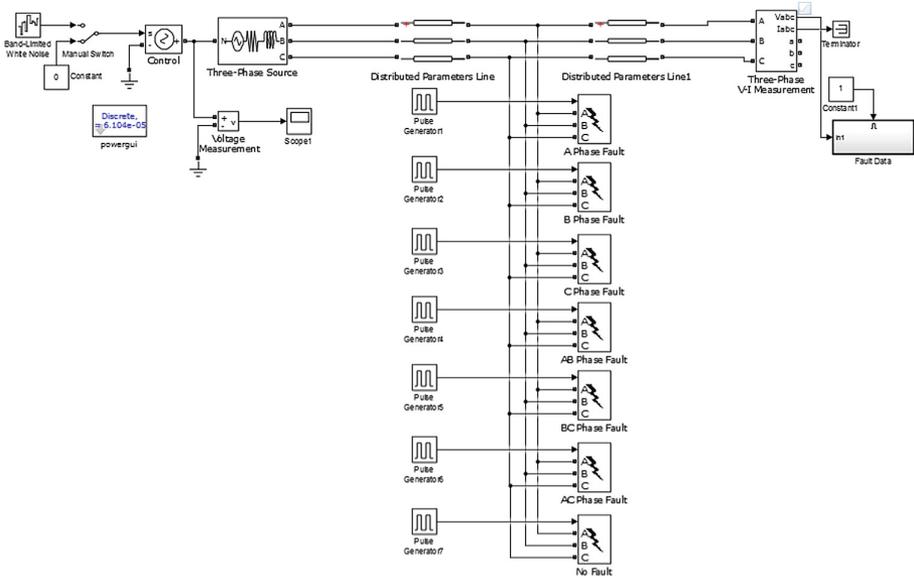


Fig. 2. The three-phase power transmission line

Table 1. Parameters of transmission lines

Parameter	Positive sequence	Zero sequence
Resistance per unit length (Ohms/km)	0.01273	0.3864
Capacitance per unit length (H/km)	12.74×10^{-9}	7.751×10^{-9}
Inductance per unit length (F/km)	0.9337×10^{-3}	4.1264×10^{-3}

The computer simulation results are shown in Tables 2, 3, 4 and 5. In Tables 2 and 3, “N” represents “no fault”; “A” represents phase A line-to-ground fault; “B” represents phase B line-to-ground fault; and “C” represents phase C line-to-ground fault. Similarly, “AB” represents phase A to B line-to-line fault; “BC” represents phase B to C line-to-line fault; and “AC” represents phase A to C line-to-line fault. The percentages on main diagonal positions are the percentage of correct classification; while all the other percentages on the off-diagonal positions are the percentage of misclassification. For example, the first column shows that for the true “no fault” case, the algorithm yields a 99.95% correct classification rate while 0.05% of the true “no fault” cases are misclassified as phase A to B line-to-line fault. The “no-fault” accuracy is obtained based on 3800 input/output data pairs and for each fault case, the accuracy of detection is obtained based on 300 input/output data pairs. Table 2 shows the confusion matrix if the data used are line current measurements; Table 3 shows similar results but with data taken on voltage signals. The average accuracy for the seven different cases is 83.33%.

Table 2. Fault identification confusion matrix based on current signals

	N	A	B	C	AB	BC	AC
N	99.95%	16.67%	8.33%	8.33%	0	0	0
A	0	83.33%	8.33%	16.33%	8.33%	0	8.33%
B	0	0	75.00%	0.33%	0	8.33%	8.33%
C	0	0	8.33%	75.00%	8.33%	0	0
AB	0.05%	0	0	0	83.33%	0	0
BC	0	0	0	0	0	91.67%	8.33%
AC	0	0	0	0	0	0	75.00%

Table 3. Fault identification confusion matrix based on voltage signals

	N	A	B	C	AB	BC	AC
N	99.95%	16.67%	8.33%	8.33%	0	0	0
A	0	83.33%	8.33%	16.67%	8.33%	0	8.33%
B	0	0	75.00%	0	0	8.33%	8.33%
C	0.05%	0	8.33%	75.00%	8.33%	0	0
AB	0	0	0	0	83.33%	0	0
BC	0	0	0	0	0	91.67%	8.00%
AC	0	0	0	0	0	0	75.33%

Table 4. Fault location determination confusion matrix based on current signals

	0 km	50 km	100 km	150 km	200 km
0 km	99.95%	22.22%	11.11%	5.56%	0
50 km	0	66.67%	16.67%	33.33%	20.22%
100 km	0	0	55.56%	0	18.67%
150 km	0	11.11%	5.56%	55.56%	5.56%
200 km	0.05%	0	11.11%	5.56%	55.56%

Tables 4 and 5 shows the simulation results on fault localization (for simplicity, only phase A line-to-ground fault is considered) using the current or voltage signals, respectively. The distances in the tables indicate the fault location. For example, “0 km” indicates the fault occurs right at the end of the power lines where measurements are taken; “50 km” indicates the fault occurs 50 km away from the endpoint (or 150 km to the power source); etc. For simplicity, only four locations are considered in this proof-of-concept study. For example, the neural network correctly identifies the fault location with an accuracy of 66.67% if the fault occurs 50 km away from the measurement data acquisition location; while the neural network misclassifies 11.11% of the fault locations as 150 km away from the point where measurement data are taken. For each distance, 450 sample pairs are generated in this simulation. In general, the fault detection accuracy decreases as the distance between fault location and measurement point increases, except at the midpoint in Table 5 (100 km away from both source and load) which needs further analysis.

Table 5. Fault location determination confusion matrix based on voltage signals

	0 km	50 km	100 km	150 km	200 km
0 km	100%	22.22%	11.11%	5.56%	0
50 km	0	66.67%	16.67%	33.33%	16.67%
100 km	0	0	55.56%	0	22.22%
150 km	0	11.11%	5.56%	61.11%	0
200 km	0	0	11.11%	0	61.11%

4 Conclusions

In this paper, we develop an approach to detect, classify, and localize different types of phase-to-ground and phase-to-phase faults in three-phase power transmission systems based on discrete wavelet transform and artificial neural networks. Satisfactory computer simulation results are obtained and presented. For future work, we plan to consider the situation when measurement data contain noise and/or outliers. Pre-processing noisy data using adaptive filtering and/or outlier detection may speed up neural network learning and improve the neural network generalization ability. More tests will be conducted to further investigate the performance of this hybrid approach.

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