ISBN 978-981-11-3671-9
Proceedings of 2017 the 7th International Workshop on Computer Science and Engineering (WCSE 2017)
Beijing, *25-27 June*, *2017*, *pp. 1078-1083*
doi: 10.18178/wcse.2017.06.187

A Fault Detection Research of Power System Transmission Line Based on Wavelet Transform

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Abstract. Fault transient signal detection is very important to make the power system work safely and improves the quality of power energy. This paper proposes a fault detection method of transmission line in power system, which based on detection of high frequency components contained in a fault signal spectrum. The Discrete Wavelet Transform (DWT) is used to detect and identify the transmission line fault as well as determine the involved phases. The entropies of wavelet coefficients of the measured bus currents are applied in the proposed technique. Simulation is performed using MATLAB program.

Keywords: fault detection, wavelet transform, entropy calculation, wavelet coefficients

1. Introduction

The importance of power system protection plays a great role in the successful operation of power system [1-3]. Traditionally, radial networks are protected using coordinated overcurrent relays whereas meshed networks using directional overcurrent relays [4]. With the expansion of the power system and consumer's higher quality requirement, the fault signal detection method must be improved greatly. Researchers have introduced wavelet analysis, mathematical morphology, and supporting vector machine into the identification of transient signals. Accordingly, progress has been made especially in the fields of faulty phase identification, power quality disturbance, lightning, temporary and permanent fault identification [5–7].

The transient waveforms of current and voltage resulting during the fault has been thoroughly discussed, and different methods were employed in analyzing such waveforms. Some researchers used neural networks in identification of fault types [8], others used wavelet analysis for fault detection and identification [9]. With further research, new theories and concepts emerge continually [12, 13]. For example, the wavelet entropy, a combination of wavelet and entropy, could describe the characteristics of a signal. This is because wavelet meets the demands of transient signal analysis and entropy is ideal for the measurement of uncertainty. Based on such transformation, the wavelet energy entropy in association with neural-fuzzy inference system is used for fault classification [14]. The wavelet entropy principle has been employed in different applications in power system [15-16]. In [17–19], wavelet transformation generated time-frequency parameters and wavelet entropy generated characteristic vector. These characteristics were put into neural network to detect the transient fault, then a fuzzy system was used to identify the fault.

This paper concludes the following contents: Section II provides the principle of wavelet entropy and calculation of wavelet entropy weight. Section III simulates a system to obtain different current signals for testing of the proposed technique. Section IV presents the testing results and gives a discussion of advanced methods for fault diagnosis of power system transmission line.

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2. The Principle of Wavelet Entropy

2.1. Wavelet transform

Transient signals are basically with high frequency and instant break. Usually, wavelet transform of transient signal is expressed by multi-revolution decomposition fast algorithm which utilizes the orthogonal wavelet bases to decompose the signal to components under different scales. It is similar to recursively filtering the signal with a high-pass and low-pass filter pair. The approximations are the high-scale, low-frequency components of the signal produced by filtering the signal by a low-pass filter. The details are the low-scale, high-frequency components of the signal produced by filtering the signal by a high-pass filter. The bandwidths of these two filters are equal. After each decomposition, the sampling frequency is reduced by half. Then recursively decompose the low-pass filter outputs to produce the components of the next stage [9, 10]. Fig. 1 shows the tree structure implementation of filter-banks for one-dimensional DWT, where g(n) stands for the high-pass filters, h(n) for the low-pass filters, and the arrows for the down sampling process.

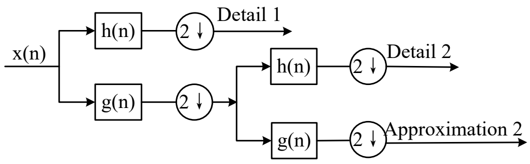

Fig. 1: Implementation of DWT using filter-banks

2.2. Calculation of wavelet entropy weight

Given a discrete signal $x(n)$ which is fast transformed at instant k and scale j with a high-frequency component coefficient $D_j(k)$ and a low-frequency component coefficient $A_j(k)$. The frequency band of the information contain in signal components $D_j(k)$ and $A_j(k)$, obtained from reconstruction are as follows [11].

$$\begin{cases} D_j(k):\left[2^{-(j+1)} f_s, 2^{-j} f_s\right] \\ A_j(k):\left[0, 2^{-(j+1)} f_s\right] \end{cases} (j=1,2,...,m) \tag{1}$$

where f_s is the sampling frequency.The original signal sequence $x(n)$ can be represented by the sum of all components as shown [11].

$$x(n) = D_1(n) + A_1(n) = D_1(n) + D_2(n) + A_2(n) = \sum_{j=1}^{J} D_j(n) + A_J(n) \tag{2}$$

Various wavelet entropy measurements were defined in [9]. In this paper, the non-normalized Shannon entropy will be employed. The non-normalized Shannon entropy is as define [11].

$$E_j = -\sum_k E_{jk} \log E_{jk} \tag{3}$$

where E_{jk} is the wavelet energy spectrum at scale j and instant k. As defined by,

$$E_{jk} = \left|D_j(k)\right|^2 \tag{4}$$

Actually, different wavelet basis functions have been proposed and selected in [20]. There are two criteria for the selection of the mother wavelet in power system relay protection. Initially, the shape and the mathematical expression of the wavelet must be set according to easy physical interpretation of wavelet coefficients. Secondly, the chosen wavelet must allow a fast computation of wavelet coefficients. The Daubechies wavelet has been proven efficient in signal analysis. And in our latter proposed scheme, the Daubechies 10 (db10) order orthogonal wavelet is employed after comparison.

3. The Proposed Algorithm

The amplitude and frequency of the test signal will change significantly as the system status varies from normal to fault, and the Shannon entropy of the signal will change accordingly. It becomes incapable of dealing with some abnormal signals while the wavelet is capable. The wavelet combined entropy can make full use of localized feature at time-frequency domain. Wavelet deals with unsteady signal while information entropy expresses signal information. The three phase current signals (i_a, i_b and i_c) and the ground current ($i_g = i_a + i_b + i_c$) are inputs of the proposed algorithm.

3.1. Fault detection and phase selection

Transient mutation signal and weak signal could be analyzed by wavelet accurately, and their fault characteristics could be extracted effectively. In the proposed algorithm, suma, sumb, sumc represent the sum of the entropy values for three phase currents respectively, and *max1=max (suma, sumb, sumc)*, *min=min (suma, sumb, sumc)*, *max2* = the remaining sum (intermediate value).The steps are as followed: Initially, enter three phase currents of a line and calculate its ground current; Secondly, the line current signal is decomposed by wavelet transform to calculate the entropy of the wavelet coefficients of each phase current; Thirdly, the sum of the absolute entropy of the wavelet coefficients of each phase is calculated and the maximum phase, the minimum phase and the intermediate phase are obtained. Finally, determine whether line fault occurs in the input current signal, confirm the fault type and the fault phase at the mean time.

3.2. Flow chart

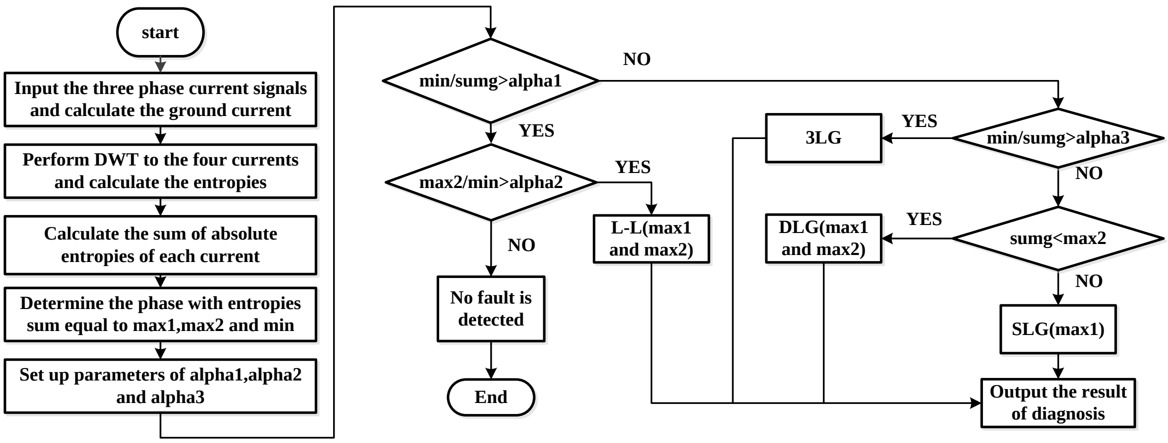

Fig. 2: Flow chart of fault detection and phase selection algorithm

The flow chart of the algorithm mentioned above is as shown in Fig.2.

3.3. Parameter setting

In total, three parameters as alpha1, alpha2 and alpha3 are set, where alpha1 and alpha3 are set for comparing min phase and sumg. When fault is not occurred in the system, the value of sumg is much smaller than that of the other three phases. Initially set alpha1 to 2.0, after fault detection, adjust alpha1 to 10.0 based on system diagnostic accuracy, which also meets the magnitude difference between min phase and sumg. When ground fault is occurred, the value of sumg will be extremely high. The parameter alpha3 is set to 1.0 to compare the value of the sumg and min phase. When phase-to-phase short-circuit fault is occurred, the current value of two phases will surge inevitably, so in order to determine whether phase short circuit is occurred, set parameter alpha2 to compare the intermediate phase max2 and the smallest phase min.

In order not to miss the possible faults, alpha2 is initially set to 5.0. According to the actual data analysis, some fault-free data will be mistakenly diagnosed as fault status. Ultimately, alpha2 is adjusted to 12.0 based on the actual data analysis process.

4. Case Study

In order to further verify the accuracy of the algorithm, the recorded data of typical moments per day and that of typical moments per year in Shandong province is specially chosen to take statistical analysis respectively.

4.1. Typical faults simulation

The proposed algorithm detects if there is a fault or the system is under normal conditions. It also determines the actual fault type from 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. At the same time, the algorithm could achieve phase selection involved in the fault. From the statistical data, only two typical faults (SLG fault and phase-to-phase short circuit fault) in the power system are detected in detail, and the concrete simulation results are given.

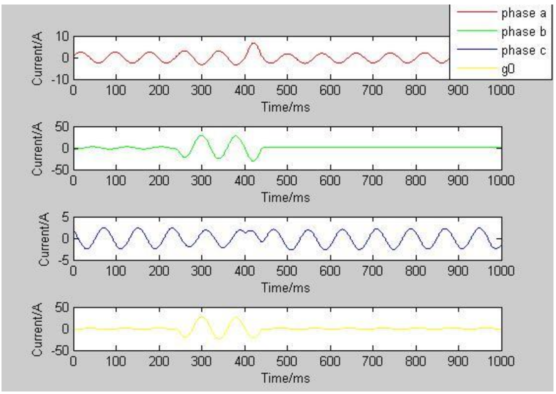

Fig. 3: B phase ground short circuit fault

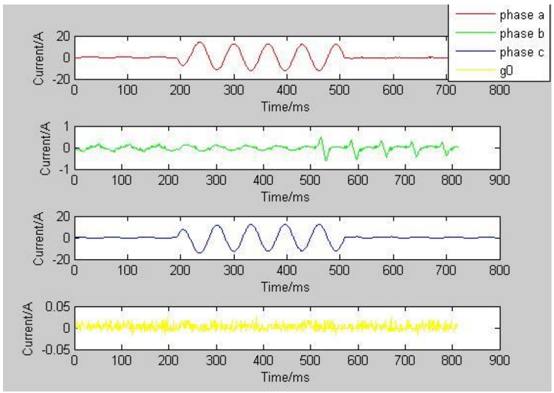

Fig. 4: AC phase-to-phase short circuit fault

In Fig. 3, it can be concluded that there is B phase ground short circuit fault. B-phase current increases at 250ms, where its amplitude increases significantly compared to that of the other two phase currents.

In Fig. 4, it can be seen that there is AC phase-to-phase short circuit fault. AC phase-to-phase current increases at 200ms, where its amplitude increases significantly compared to that of B-phase current.

4.2. Testing results

The sample data in Table 1 are selected from a multiple-fault-occurred representative day of Shandong province. Analysis based on wavelet transform and diagnostic results of the recorded data are as shown.

Table 1: Analysis based on wavelet transform and diagnostic results of a representative day

Line	suma	sumb	sumc	sumg	diagnostic result
1	1.6767E-23	2.0632E-23	2.5910E-23	5.2299E-26	Fault-free
2	3.4010E-23	5.2689E-23	1.7875E-23	7.9562E-26	Fault-free
3	8.4717E-23	8.6799E-23	8.5597E-23	2.3941E-27	Fault-free
4	8.2797E-23	9.9444E-23	1.0638E-22	2.2932E-27	Fault-free
5	1.3820E-23	1.9728E-23	2.9062E-23	9.1531E-26	Fault-free
6	7.5909E-23	8.8152E-23	7.1935E-23	2.4656E-27	Fault-free
7	8.2111E-23	1.0053E-22	6.8183E-23	2.0860E-27	Fault-free
8	6.8338E-23	6.7814E-23	7.1928E-23	4.8781E-25	Fault-free
9	1.1103E-24	7.4640E-24	1.0449E-24	1.2576E-24	Fault-free
10	8.2648E-22	5.5054E-25	8.4153E-22	2.5489E-27	AC phase-to-phase fault
11	1.6007E-22	2.5532E-21	1.0525E-22	1.9851E-21	B phase-to-ground fault
12	1.2759E-23	2.3765E-22	2.5886E-23	1.4774E-22	B phase-to-ground fault
13	2.5194E-22	2.0499E-22	1.8481E-22	8.9668E-26	Fault-free
14	3.3441E-24	5.2703E-24	3.9194E-24	5.6010E-25	Fault-free
15	2.2754E-22	2.2714E-22	2.2037E-22	3.0060E-26	Fault-free
16	1.5570E-22	2.5008E-21	1.0541E-22	1.9570E-21	B phase-to-ground fault
17	1.5323E-22	2.5133E-21	1.0356E-22	1.9652E-21	B phase-to-ground fault

It can be seen from Table 1 that the sum of the absolute entropy of the three-phase current of lines 10, 11, 12, 16, 17 differ significantly from the other lines on the order of magnitude. It could be concluded that faults occur in the above lines. The algorithm proposed above is used to determine the diagnostic results with the help of MATLAB program. Compared with the final fault report from the power supply company in the region, all the 17 fault detection results in the table are correct by the algorithm. The correctness rate is 100%, significantly verifies the algorithm.

5. Conclusion

Compared with traditional relatively independent diagnosis of line fault and phase fault, this paper proposes a line-phase combined algorithm based on wavelet transform to quickly detect whether sudden changes occur and determine the fault location and the fault type. The algorithm proposed in this paper is simple and fast, and works well in assisting schedule personnel to determine fault location and fault type.

However, there are still some future work that could be continued. The parameters set in the algorithm are from the actual data acquisition, which may not be accurate due to the limitation of sample amount. Also, the two-phase short-circuit ground fault and three-phase short-circuit ground fault have not been diagnosed in the statistical data we got, thus the simulation of the specific example could not be given in this paper.

Further work could perform in simulating larger amount of data, setting the parameters with enough samples, improving the diagnostic accuracy, and setting the upper and lower bounds of the parameters to improve the detection accuracy.

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