Early detection for short-circuit fault in low-voltage systems based on fractal exponent wavelet analysis

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Abstract: - By combining wavelet transform (WT) with fractal theory, a novel approach is put forward to detect early short-circuit fault. The application of signal denoising based on the statistic rule is brought forward to determine the threshold of each order of wavelet space, and an effective method is proposed to determine the decomposition adaptively, increasing the signal-noise-ratio (SNR). In a view of the inter relationship of wavelet transform and fractal theory, the whole and local fractal exponents obtained from WT coefficients as features are presented for extracting fault signals. The effectiveness of the new algorithm used to extract the characteristic signal is described, which can be realized by the value of the fractal dimensions of those types of short-circuit fault. In accordance with the threshold value of each type of short-circuit fault in each frequency band, the correlation between the type of short-circuit and the fractal dimensions can be figured to perform extraction. This model incorporates the advantages of morphological filter and multi-scale WT to extract the feature of faults meanwhile restraining various noises. Besides, it can be implemented in real time using the available hardware. The effectiveness of this model was verified with the simulation results.

Key-Words: - Power system, early detection, short-circuit fault, fractal theory, wavelet transform

1 Introduction

Although utility industry restructuring, increasing system capacity needs, and technology advancements are leading in a widespread introduction of distributed generation, this does not mean that the traditional model of centralized electric power generation and delivery is abandoned. Moreover, the introduction of natural gas, the deregulation of the electricity market, environmental concerns and specific investment policies lead to a simultaneous development of large scale units with small customer-specifiedunits.Technological mprovements lead to lower cost per power both for small and large units, while taking into consideration emission reduction policies.

But, irrelevant from the energy system expansion and the extent of the distributed generation penetration, power quality issues and security constraints for the network, the connected devices and the people, are in the first priority of the transmission and distribution system construction. This demands a proper selection and combination of security equipment. For large disturbances, which are triggered by some initial fault, the network can be led to instability in case of human fault, malfunction or unsuitable equipment. It is duty of power system analysts and planners to specify the proper equipment selection by carrying out simulation analysis of all possible faults. The system behavior before and during a possible fault has to be monitored and analyzed.

Furthermore, the initial network structure was based on the basis of carrying out specific load demands and power generation capacities. The reconstruction of the power generation system may violate specific security limits such the thermal rating of the network lines in case of a short circuit fault. The magnitude of a short-circuit current in a three-phase a.c. system (maximum or minimum short-circuit current) at any location, depends primarily on the network configuration, the generators and the motors in operation and secondarily on the operational stage of the network before the short circuit. This requires the network examination in every system expansion concerning the generating or the active and reactive power consuming units because there may needed a corrective action in certain constrained systems.

Short-circuit is one of the most frequent case of external faults. When a power device works under short-circuit condition, it is subjected to high surge current with full anode-cathode voltage. After a short delay time ，if short-circuit mode remains applied, the power device may he driven out of its Safe Operating Area (SOA) and may be destroyed. Delay time is usually implemented in power device protection in order to avoid unwished power switch turn-off due to transient state conditions.

The wavelet transform provides such a framework for the analysis of a signal that can locate energy in both the time and scale domain close to the theoretical bound given by the Heisenberg's uncertainty principle. Thus, multiresolution analysis based on wavelet transform is an excellent tool in providing spatial-frequency decomposition[1]-[5]. Fractals are mathematical sets that process high degrees of geometrical complexity and can model numerous natural phenomena[6], [7]. Fractal provides a proper mathematical framework to study the irregular and complex shapes that exist in nature. An essential feature of fractal geometry is that it enables the characterization of irregularity that may not be treated generally in Euclidean geometry.

In this paper, an alternative approach is proposed, which combines the advantages of the WT with the ones from the fractal dimension (FD) analysis, in order to achieve superior performance in the early detection for short-circuit fault. In particular, the efficiency of the FD analysis is transferred to the WT domain as a means that values the WT coefficients according to their significance in the signal structure.

2 Wavelet transform and fractal theory

2.1 WT-Based multiresolution analysis

The mathematics of the wavelet transform were extensively studied and the multiresolution analysis was introduced by Mallat. Basically, a wavelet is a function $\psi \in L^2(R)$ with a zero average

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0 \tag{1}$$

The continuous wavelet transform (CWT) of a signal $x(t)$ is then defined as

$$CWT\psi_x(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right) \tag{2}$$

where $\psi(t)$ is called the mother wavelet, the asterisk denotes complex conjugate, a and b ($a, b \in R$)are scaling (dilation) and translation parameters, respectively. The scale parameter a will decide the oscillatory frequency and the length of the wavelet, the translation parameter b will decide its shifting position.

In a practical application, we will use the discrete wavelet transform (DWT) instead of the CWT. This is implemented by using discrete values of the scaling parameter and translation parameter. To do so, set $a = a_0^m$ and $b = nb_0 a_0^m$, then we get

$$\psi_{m,n}(t) = a_0^{-m/2}\psi(a_0^{-m}t - nb_0) \tag{3}$$

where $m, n \in Z$, and m indicating frequency localization and n indicating time localization. Generally, we can choose $a_0 = 2$ and $b_0 = 1$. This choice will provide a dyadic-orthonormal wavelet transform and provide the basis for multiresolution analysis.

In MRA, any time series $x(t)$ can be completely decomposed in terms of the approximations, provided by scaling functions $\phi_m(t)$ and the details, provided by the wavelets $\psi_m(t)$, where $\phi_{m,n}(t)$ and $\psi_{m,n}(t)$ are defined as the following:

$$\phi_{m,n}(t) = 2^{-m/2}\phi(2^{-m}t - n)$$
$$\psi_{m,n}(t) = 2^{-m/2}\psi(2^{-m}t - n) \tag{4}$$

The scaling function is associated with the low-pass filters with filter coefficients $\{h(n), n \in Z\}$, and the wavelet function is associated with the high-pass filters with filter coefficients $\{g(n), n \in Z\}$. The so-called Two Scale Equations (TSE) give rise to these filters

$$\phi(t) = \sum_n h(n)\sqrt{2}\phi(2t - n)$$
$$\psi(t) = \sum_n g(n)\sqrt{2}\phi(2t - n) \tag{5}$$

There are some important properties of these filters

$$\sum_n h(n)^2 = 1$$
$$, \sum_n g(n)^2 = 1 \quad , \sum_n h(n) = \sqrt{2} \quad , \sum_n g(n) = 0 \tag{6}$$

Filter $g(n)$ is an alternating flip of the filter $h(n)$, which means there is an odd integer N such that

$$g(n) = (-1)^n h(N - n) \tag{7}$$

Daubechie gives a detailed discussion about the characteristics of these filters and how to construct them. The decomposition procedure starts with passing a signal through these filters. The approximations are the low-frequency components of the time series and the details are the high-frequency components.

Multiresolution analysis leads to a hierarchical and fast scheme. This can be implemented by a set of successive filter banks as follows. Considering the filter bank implementation in (5),(6) and (7), the relationship of the approximation coefficients and detail coefficients between two adjacent levels are given as

$$cA_j(k) = \sum_n h(2k-n)cA_{j-1}(n) \tag{8}$$

$$cD_j(k) = \sum_n g(2k-n)cA_{j-1}(n) \tag{9}$$

where cA_j and cD_j represent the approximation coefficients and detail coefficients of the signal at level j, respectively; $h(n)$ and $g(n)$ are the low-pass and high-pass filters; k is the coefficient index at each decomposition level.

In this way, the decomposition coefficients of MRA analysis can be expressed as

$$\begin{aligned}&[A_0] \leftrightarrow [cA_0, cD_1] \leftrightarrow [cA_2, cD_2, cD_1]\\ &\leftrightarrow [cA_3, cD_3, cD_2, cD_1] \leftrightarrow \cdots\end{aligned} \tag{10}$$

which correspond to the decomposition of signal as

$$\begin{aligned}x(t) &= A_1(t) + D_1(t) = A_2(t) + D_2(t) + D_1(t)\\ &= A_3(t) + D_3(t) + D_2(t) + D_1(t) = \cdots\end{aligned} \tag{11}$$

where $A_i(t)$ is called the approximation at level i, and $D_i(t)$ is called the detail at level i. Since both the high pass filter and the low pass filter are half band, the MRA decomposition in frequency domain for a signal sampled with the sample frequency can be demonstrated in the down sampling with a factor of 2.

2.2 Fractal dimension theory

The term "fractal dimension" can more generally refer to any of the dimensions commonly used for fractals characterization (e.g., capacity dimension, correlation dimension, information dimension, Lyapunov dimension, and Minkowski-Bouligand dimension). In other words, the FD is a measure of how "complicated" a self-similar figure is. To this end, the FD can be considered as a relative measure of the number of basic building blocks that form a pattern. Consequently, the FD could reflect the signal complexity in the time domain. This complexity could vary with sudden occurrence of transient signals, such as short-circuit fault signal; hence, the FD could provide a means that tracks the location of the fault signal in the time series. It must be noted that the estimation of the FD adopted here is derived from an operation directly on the signal and not on any state space. This means that the data series does not have to be embedded into higher dimensional space for the FD estimation; hence, the FD has fast computational implementation.

2.2.1 Katz's definition of FD

According to Katz, the FD of a curve defined by a sequence of N points is estimated by

$$FD^K = \frac{\log_{10}(n_s)}{\log_{10}\left(\frac{d}{L_c}\right) + \log_{10}(n_s)} \tag{12}$$

where the K indicator denotes the Katz's definition of FD; L_c is the total length of the curve, realized as the sum of distances between successive points, i.e.,

$$L_c = \sum_{i=1}^{N-1} dist(i, i+1) \tag{13}$$

where $dist(i, j)$ is the distance between the i and j points of the curve; d is the diameter estimated as

$$d = \max[dist(i, j)];\ i \neq j,\ i, j \in [1, N] \tag{14}$$

for curves that do not cross themselves, usually, the d diameter is estimated as the distance between the first point of the sequence and the point of the sequence that provides the farthest distance, i.e.,

$$d = \max[dist(1, i)];\ i, j \in [2, N] \tag{15}$$

and n_s ns is the number of steps in the curve, defined as

$$n_s = \frac{L_c}{\bar{a}} \tag{16}$$

where $\bar{a}$ a denotes the average step, i.e., the average distance between successive points. In this way, a general unit or "yardstick" is formed that eliminates the dependence of the FD estimates derived by (12) on the measurement units used.

2.2.2 Sevcik's definition of FD

Sevcik uses the following definition for the FD of an N-sample curve

$$FD^S = 1 + \frac{\ln(L_c)}{\ln(2(N-1))} \tag{17}$$

where the S indicator denotes the Sevcik's definition of FD and L_c is defined as in (13). Before applying (17), Sevcik proposes, for convenience, linear transformations of the waveform, in order to transform it into a normalized space where all axes are equal. He proposes normalization of every point in the abscissa as

$$x_i^* = \frac{x_i}{x_{\max}},\ i = 1,...,N \quad (18)$$

where $x_i, i = 1,...,N$, are the original values of the abscissa and $x_{\max} = \max(x_i)$, and ordinate normalized as

$$y_l^* = \frac{y_i - y_{\min}}{y_{\max} - y_{\min}} \quad (19)$$

where $y_i, i = 1,...,N$, are the original values of the ordinate, $y_{\max} = \max(y_i)$, and $y_{\min} = \min(y_i)$.

Both the above two FD definitions, given by (12) and (17), respectively, were alternatively realized within the WT-FD filter structure. Nevertheless, since the differences in the amplitude between the WT coefficients in the WT scales were of great importance, the normalization of (18) and (19) was not adopted in the implementation of (17) in the WT-FD filter, because it significantly reduced these differences. Instead, for keeping the same peak peeling algorithm in both realizations of the FD, and without affecting the dynamic range of the $FD^{K,S}$ estimates, associated with the dynamic range of the relevant WT coefficients, the following ordinate transformation was applied:

$$FD^{K,S} = FD_{orig}^{K,S} - m_{FD} + 1 \quad (20)$$

where $FD_{orig}^{K,S}$ are the FD estimates of the curve given by (12) or (17), and $m_{FD} = \min(FD_{orig}^{K,S})$. With (9), the $FD^{K,S}$ estimates have always minimum value equal to 1.0.

2.2.3 FD estimation

The FD, defined either by (12) or (17), is estimated

$$W_L = \mathrm{int}(0.006 f_s) \quad (21)$$

where int $(\cdot)$ indicates the integer part of the argument and f_s is the sampling frequency used in the acquisition of the sound signals. The constant 0.006 results in valid FD peaks, since low values of W_L generate too many false (not reliably estimated) FD peaks, while high values of W_L result in smoothed FD time series, merging the sharp peaks, hence, reducing the required peak resolution in the FD domain. This W_L-sample window is one-sample shifted along the N-sample input vector, with $W_L << N$, in order to obtain point-to-point values of the estimated FD. The estimated FD, using either (12) or (18), over each segment of the input vector obtained with the sliding window is assigned to its midpoint. In this way, the final sequence of the FD has a total length of $N - W_L + 1$ samples. This length is extended to comply with the N-sample length of the original input vector, assigning the FD and FD $N - W_L + 1$ estimated values to the first and last half of the $W_L - 1$ missing values, respectively.

2.3 The proposed approach

The main thrust of the proposed WT-FD filter is the more enhanced selection of the WT coefficients that correspond to the short-circuit during the employed MRD-MRR procedure, compared to that of the wavelet transform b-ased stationary-nonstationary (WTST-NST) filter. For ease of reference, the WTST-NST filter is epitomized here.

The WTST-NST filter is a wavelet domain filtering technique that characterizes the WT coefficients with respect to their amplitude. In particular, the WTST-NST filter employs the MRD-MRR scheme to produce the WT coefficients at different analysis scales, and categorizes the most significant WT coefficients at each scale, with amplitude above some threshold, as the ones that correspond to the signal of interest, and the rest, as the ones that correspond to the background noise. Consequently, a wavelet domain separation of the WT coefficients corresponding to the signal of interest and the background noise, respectively, is used to offer a domain separation of the same signals. With an iterative procedure, the WTST-NST filter constructs refined versions of the signal of interest, resulting, after a stopping criterion is met, in the finally de-noised short-circuit signal.

The proposed WT-FD filter overcomes the requirement of the WTST-NST filter for empirical setting of a multiplicative parameter in the definition of its threshold, providing a different perspective in the categorization of the WT coefficients. In particular, it employs the FD analysis to construct an efficient way of thresholding. This use of the FD is motivated by the work of Hadjileontiadis and Rekanos, where they used the FD^K to successfully detect the transient signal in the sound recordings. Their FD-based detector, namely FDD, resulted in efficient and accurate detection of the short-circuit in the time domain. However, the FDD did not provide with short-circuit signals extracted from the background noise. In the proposed WT-FD filter, the detection ability of the FDD scheme is applied not in the time domain, but in the WT one. In this way, not only the detection but the extraction, as well, of the short-circuit signals from the background noise is achieved, by reconstructing the signal of short-circuit through the WT coefficients efficiently selected by the FDD.

3 Simulation Results and analysis

Short circuit faults in electric power can be mainly divided into four types, i.e. single-phase ground fault, two-phase fault, two-phase ground fault, three-phase ground fault. This paper emphasizes on the two-phase fault and the selected mother wavelet is Meyer wavelet.

In this section, the simulation data was generated in Power system toolbox of Matlab/Simulink. The method can acquire the variation rule of shout-circuit in distribution power system for further analysis. The short-circuit current is decomposed into four levels by Meyer wavelet, and based on the feature extraction technology of wavelet transform, the WT-FD of the fourth level detailed components is threshold for short-circuit fault determination. In distribution power system, the power supply voltage angle or the current angle has large impact on the short-circuit current fluctuation process, and fault initial phase is considered as an important factor. Without loss of generality, A phase and B phase are fault phases and C phase is the normal phase. Fig.1 and Fig.2 are the three phase current and WT-FD calculation results, respectively. CWD represents complex wavelet decomposition. Table 1 shows the maximum of Signal and WT-FD of two-phase short-circuit and we can see that: the WT-FD of A phase fault current and B phase fault current are different distinctly from the C phase normal current. The value in Table 1 is normalized value.

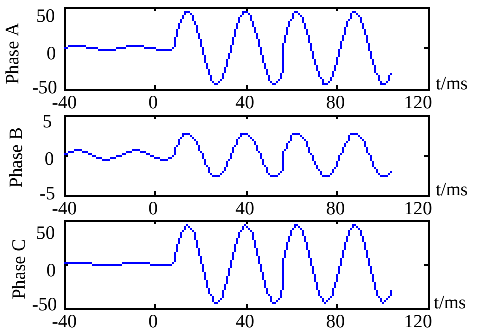

Fig. 1 Waveform of phase current under two-phase short-circuit

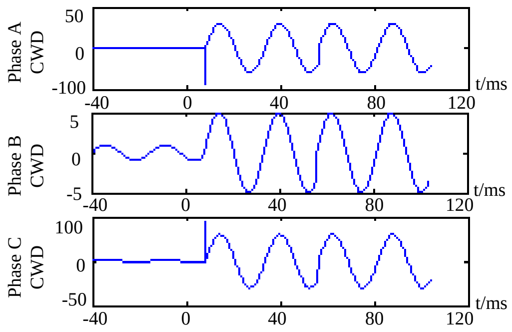

Fig. 2 CWD of phase current under two-phase short-circuit

Table1 The maximum of phase current and WT-FD under two-phase short-circuit

Phase Angle	Phase Sequence	0	30	60	90	120	150	165
Current	A	27.56	27.58	27.62	27.59	27.66	27.54	27.88
	B	25.83	25.84	25.87	26.02	26.16	25.87	26.12
	C	4.93	4.92	4.93	5.02	5.06	5.01	5.04
CWD	A	88.49	97.56	77.97	40.46	27.59	57.21	80.21
	B	89.01	98.43	76.97	41.31	25.61	57.23	82.20
	C	4.92	4.88	4.93	5.02	5.04	4.96	4.97

4 Conclusions

In this paper, the WT-FD filter, a wavelet-based filtering scheme that employs fractal dimension thresholding is proposed evaluated to detect the short circuit in distribution power system and proved to be a very promising tool for the enhancement of the early fault prediction. The employment of the FD in the WT domain provides an effective selection of the WT coefficients. Quantitative and qualitative analysis of the simulation results, show very reliable and robust performance, despite the differences in the morphology of the various types of the input signals.

The advantage of using the wavelet-based fractal analysis is indeed twofold. First, we analyze the nonstationary signal using the wavelet transform. Then, the time-frequency information contents obtained with the wavelet transform will be used to estimate the fractal value as detailed in the method section to characterize the signal. The estimation of the Hurst exponent (or the fractal dimension) is nothing more than a representation of the variances of the wavelet coefficients at each scale, which provides valuable information about the variance progression over the wavelet scales.

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