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Localization of Faults in High Voltage Underground Cables by Wavelet Transform

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Abstract

In this paper, a technique for identifying the phase with fault appearance in high voltage underground cable is presented. The Wavelet transform has been employed to extract high frequency components superimposed on fault signals simulated using MATLAB. It is found that the proposed method can indicate the fault types with satisfactory accuracy.

Key words: *ug cable, wavelet, faults, high voltage*

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I. INTRODUCTION

This paper deals with the identification and classification of faults in high voltage radial UG cables by wavelet transform. It presents the use of wavelet as a pattern classifier to perform the tasks of different fault identification and classification .In this work the cable model is taken and the different faults in the cable were identified and classified by wavelet and are compared. The under ground system is very important for distribution systems especially in metropolitan cities, air port and defense service The UG system provides a large capacity in transmission and no harm from visual harassment. How ever, it is difficult than those of over head transmission systems. In ordered to minimize such defectives of the faulted UG systems, the design and construction should be optimized In that fault detection, classification and also location to become easy and reliable. This wavelet analysis reduces the effect of system variables such as fault resistance, fault type and fault inception angle. The result show that the proposed technique is able to offer high accuracy in fault classification tasks

II. THEORY OF WAVELET ANALYSIS

Wavelets are functions that satisfy certain requirements. The very name *wavelet* comes from the requirement that they should integrate to zero, 'waving' above and below the *x*-axis. The diminutive connotation of *wavelet* suggests the function has to be well localized. Other requirements are technical and needed mostly to ensure quick and easy calculation of the direct and inverse wavelet transform. Compared with traditional Fourier method, there are some important differences between them. First Fourier basis functions are localized in frequency but not in time while wavelets are localized in both frequency (viadilation) and time (via translation). Moreover, wavelets can provide multiple resolutions in time and frequency. Second, many classes of functions can be represented by wavelets in more compact way. For example, functions with discontinuities and functions with sharp spikes usually take substantially fewer wavelet basis functions than sine-cosine basis functions to achieve a comparable approximation. In this section a brief theory of wavelet transformation has been explained. To develop a better insight a comparison between wavelet transform and fourier transform has been made.

2.1 Fourier Transforms

The Fourier transforms utility lies in its ability to analyze a signal in the time domain for its frequency content. The transform works by first translating a function in the time domain into a function in the frequency domain. The signal can then be analyzed for its frequency content because the Fourier coefficients of the transformed function represent the contribution of each sine and cosine function at each frequency. An inverse

Fourier transform does just what you'd expect; transform data from the frequency domain into the time domain.

$$F(\omega) = F\{f(t)\} = {}_{-\infty}\int^{\infty} e^{-i\omega t} f(t)\, dt \qquad (3.1)$$

2.2 Discrete Fourier Transforms

The discrete Fourier transform (DFT) estimates the Fourier transform of a function from a finite number of its sampled points. The sampled points are supposed to be typical of what the signal looks like at all other times. The DFT has symmetry properties almost exactly the same as the continuous Fourier transform. In addition, the formula for the inverse discrete Fourier transform is easily calculated using the one for the discrete Fourier transform because the two formulas are almost identical.

2.3 Windowed Fourier Transforms

If *f(t)* is a non periodic signal, the summation of the periodic functions, sine and cosine, does not accurately represent the signal. You could artificially extend the signal to make it periodic but it would require additional continuity at the endpoints. The windowed Fourier transform (WFT) is one solution to the problem of better representing the non periodic signal. The WFT can be used to give information about signals simultaneously in the time domain and in the frequency domain. With the WFT, the input signal *f(t)* is chopped up into sections, and each section is analyzed for its frequency content separately. If the signal has sharp transitions, one can window the input data so that the sections converge to zero at the endpoints. This windowing is accomplished via a weight function that places less emphasis near the interval's endpoints than in the middle. The effect of the window is to localize the signal in time.

2.4 Fast Fourier Transform

To approximate a function by samples, and to approximate the Fourier integral by the discrete Fourier transform, requires applying a matrix whose order is the number sample points *n.* Since multiplying an n X n matrix by a vector costs on the order of 2^n arithmetic operations, the problem gets quickly worse as the number of sample points increases. However, if the samples are uniformly spaced, then the Fourier matrix can be factored into a product of just a few sparse matrices, and the resulting factors can be applied to a vector in a total of order $n\log n$ arithmetic operations. This is the so-called *fast Fourier transform* or FFT.There are many types of wavelets [9,10], such as Harr, Daubechies 4, Daubechies 8, Coiflet 3, Symmlet 8 and so on. One can choose between them depending on a particular application. As with the discrete Fourier transform, the wavelet transform has a digitally implementable counterpart, the discrete wavelet transform (DWT). If the ‘discrete’ analysis is pursuing on the discrete time, the DWT is defined as

$$C(j,k) = \sum_{n\in Z} s(n) g_{j,k}(n) \qquad (j\in N, k\in Z)$$

where, $s(n)$ is the signal to be analyzed and $g_{i,k}(n)$ is discrete wavelet function, which is defined by

$$g_{j,k}(n) = a_0^{-j/2} g(a_0^{-j} n - k b_0)$$

Select a_0 and b_0 carefully, the family of scaled and

Shifted mother wavelets constitute an orthonormal basis of $l^2(Z)$ (set of signals of finite energy). When simply choose a_0 = 2and $b0$=1, a dyadic-orthonormal wavelet transform is obtained. With this choice, there exists an elegant algorithm, the multi resolution signal decomposition (MSD) technique [11], which can decompose a signal into levels with different time and frequency resolution. At each level *j*, approximation and detail signals *Aj*, *Dj* can be built. The words’ approximation’ and ‘detail’ are justified by the fact that *Aj* is an approximation of A_{j_1} taking into account the ‘low frequency’ of A_{j_1}, whereas the detail *Dj* corresponds to the ‘high frequency’ correction. The original signal can be considered as the approximation at level 0.The coefficients *C* (*j*,*k*) generated by the DWT are something like the ‘resemblance indexes’ between the signal and the wavelet. If the index is large, the resemblance is strong, otherwise it is slight. The signal then can be represented by its DWT coefficients as

$$s(n) = \sum_{j\in N} \sum_{k\in Z} C(j,k) g_{j,k}(n)$$

When fix *j* and sum on *k*, a detail *Dj* is defined as

$$D_j(n) = \sum_{k\in Z} C(j,k) g_{j,k}(n)$$

Then sum on *j*,the signal is the sum of all the details

$$s(n) = \sum_{j \in N} D_j(n)$$

Take a reference level called *J*, there are two sorts
of details. Those associated with indices *j*5*J* correspond to the scales 2*j*52*J*, which are the fine details. The others, which correspond to *j*\J, are the coarser details. If these latter details are grouped into

$$A_J = \sum_{j > J} D_j$$

Which defines an approximation of the signals? Connect the details and an approximation, the equality

$$s = A_J + \sum_{j \le J} D_j$$

Which signifies that *s* is the sum of its approximation A_J and of its fine details. The coefficients produced by DWT, therefore, can be divided into two categories: one is detail coefficient, the other is approximation coefficient. To obtain them, MSD provides an efficient algorithm known as a two channel sub-band coder using quadrature mirror filters [12]. Then the detail part is still represented by wavelets, which can be regarded as series of band-pass filters, whereas the approximation is represented by the dilation and translation of a scaling function, which can be regarded as a low-pass filter.

III. METHOD OF EVALUATION

There are many types of wavelets [9,10], such as Harr, Daubechies 4, Daubechies 8, Coiflet 3, Symmlet 8 and so on. One can choose between them depending on a particular application. As with the discrete Fourier transform, the wavelet transform has a digitally implementable counterpart, the discrete wavelet transform (DWT). If the 'discrete' analysis is pursuing on the discrete time, the DWT is defined as

$$C(j,k) = \sum_{n \in Z} s(n) g_{j,k}(n) \qquad (j \in N, k \in Z)$$

where, *s*(*n*) is the signal to be analyzed and $g_{i,k}(n)$ is discrete wavelet function, which is defined by

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Shifted mother wavelets constitute an orthonormal basis of $l^2(Z)$ (set of signals of finite energy). When simply choose a_0 = 2and *b*0=1, a dyadic-orthonormal wavelet transform is obtained. With this choice, there exists an elegant algorithm, the multi resolution signal decomposition (MSD) technique [11], which can decompose a signal into levels with different time and frequency resolution. At each level *j*, approximation and detail signals *Aj*, *Dj* can be built. The words' approximation' and 'detail' are justified by the fact that *Aj* is an approximation of A_{j_1} taking into account the 'low frequency' of A_{j_1}, whereas the detail *Dj* corresponds to the 'high frequency' correction. The original signal can be considered as the approximation at level 0.The coefficients *C* (*j*,*k*) generated by the DWT are something like the 'resemblance indexes' between the signal and the wavelet. If the index is large, the resemblance is strong, otherwise it is slight. The signal then can be represented by its DWT coefficients as

$$s(n) = \sum_{j \in N} \sum_{k \in Z} C(j,k) g_{j,k}(n)$$

When fix *j* and sum on *k*, a detail *Dj* is defined as

$$D_j(n) = \sum_{k \in Z} C(j,k) g_{j,k}(n)$$

Then sum on *j*,the signal is the sum of all the details

$$s(n) = \sum_{j \in N} D_j(n)$$

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of details. Those associated with indices *j*5*J* correspond to the scales 2*j*52*J*, which are the fine details. The others, which correspond to *j*\J, are the coarser details. If these latter details are grouped into

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By using wavelets analysis, sub-band information can be extracted from the simulated transients, which contain useful fault features. By analyzing these features of the detail signals, different types of fault can be detected and classified. As mentioned earlier, the choice of analyzing wavelets plays a significant role in fault detect ion and identification. Since Daubechies 8 is localized, i.e. compactly supported, in time, it is good for short and fast transient's analysis. After examinations of several types of wavelet, Daubechies 8 is chosen in this scheme.

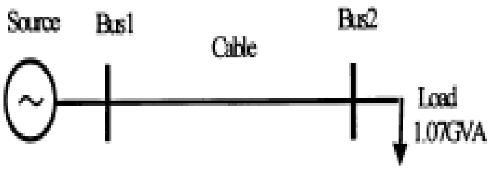

Fig -1Configuration of a 400 kV cable system.

The wavelet levels to be selected must best reflect the fault characteristics under various system and fault conditions. In this respect, according to the analyses of different wavelet levels of current waveform and the level 4 (*D*4) and level 7 (*D*7) details, are utilized to extract some useful features. This is because the level 4 details generally reflect the dominant non-frequency transient generated by faults. Since level7 details contain most of the fundamental harmonic, which is of 50 Hz in this system, the sum of three phase of them (*D*9a, *D*9b, and *D*9c) have similar characteristics of zero component which can be used to differ phase-to-ground fault and phase-phase fault, two-phase to ground fault and three-phase fault **Figs. 6–8** present wavelet analysis results of other types of fault, which are two-phase fault, two phase to ground fault and three phase fault, respectively.

IV. WAVELET ANALYSIS OF FAULT IDENTIFICATION

After analyzing numerous fault transients simulated by using wavelet transform, several fault related features have been identified. Based on these information, a novel fault detection and classification scheme as shown in fig 3.1 – 3.7 is presented, which has been summarized as the following

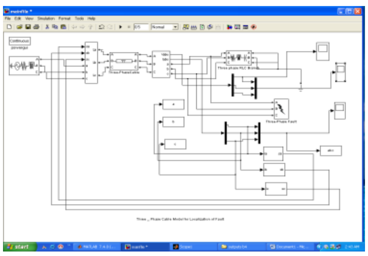

Fig 4.1 Matlab simulink model of Thee Phase cable Model

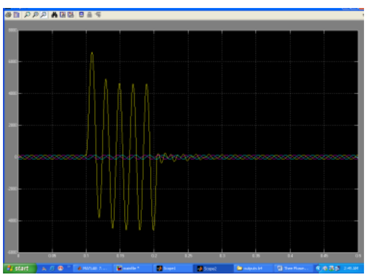

Fig 3.1 Fault current by LG fault

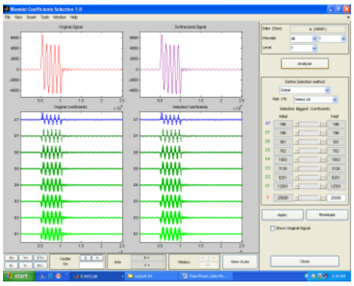

Fig 3.2Fault current by LG fault By Wavelet

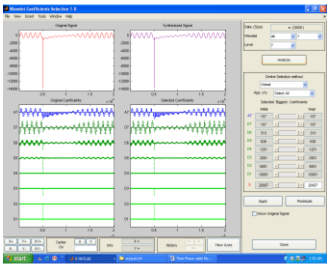

Fig 3.3 Fault current through Phase A(LG-Fault)

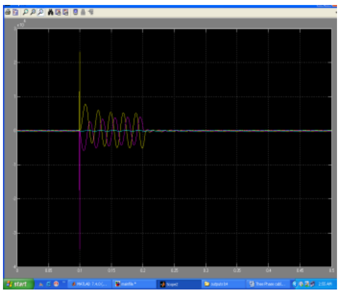

Fig 3.4Fault current by LLG Fault

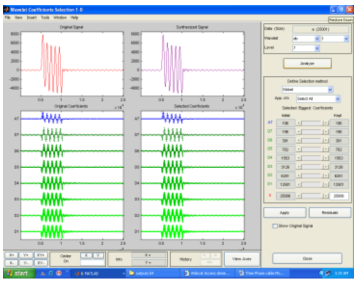

Fig 3.5 Fault current by LLG Fault By wavelet

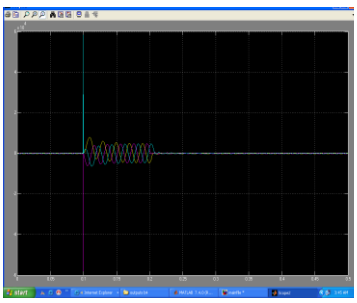

Fig 3.6 Fault current by LLLG

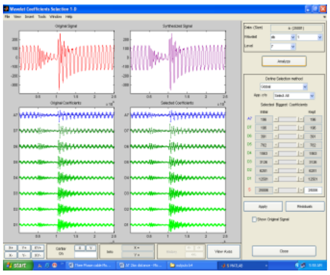

Fig 3.7 Fault current by LLLG by waveletAT 2km distance

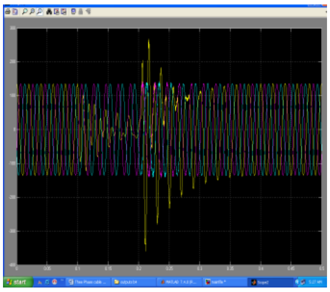

Fig 4.1 fault current for LG fault

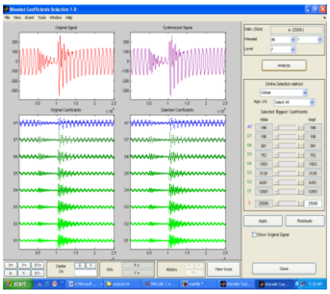

Fig 4.2 LG fault current by wavelet

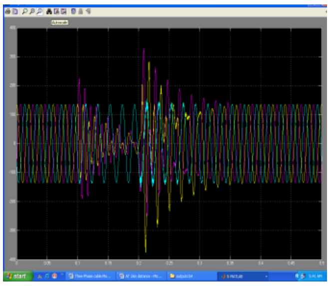

Fig 4.3Fault current for LLG fault

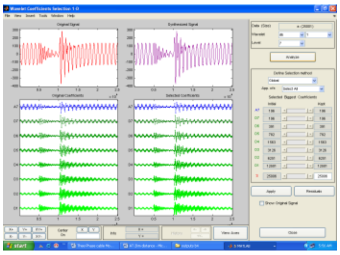

Fig 4.4 Fault current for LLG fault By wavelet

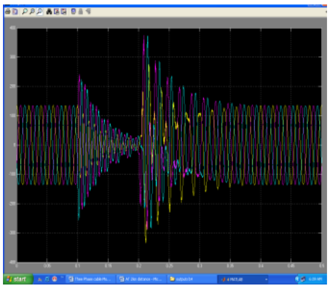

Fig 4.5 Fault current for three phase fault-(LLLG)

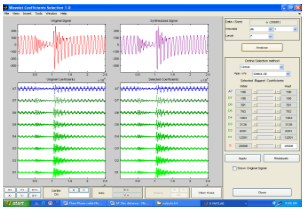

Fig 4.6Fault current for LLLG fault by wavelet

The fault analysis on a high voltage UG cable is carried by both conventional simulink and wavelet technique at a distance of 2 km from the supply system and the results are shown in fig from 4.1 to 4.6.The simulation results are plotted with time Vs magnitude of fault current.

V. CONCLUSION

This paper presents the analysis of very fast transient over voltages (VFTOs) in transformer when subjected to transients faults .The analysis has been carried by wavelet transform for different operating times of switching conditions. The transient faults are created by providing the disconnecting switches. The transformer is modeled in MATLAB similink with switching conditions. At different cycles the simulation was carried and the resultant voltage responses are shown. The fault analysis on a high voltage UG cable is carried by both conventional simulink and wavelet technique at a distance of 2 km from the supply system and the results are shown in fig from 4.1 to 4.6.The simulation results are plotted with time Vs magnitude of fault current.

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BIOGRAPHIES AND PHOTOGRAPHS

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4)Bhumanapally.Ravindhranh Reddy, Born on 3rd September, 1969. Got his B.Tech in Electrical & Electronics Engineering from the J.N.T.U. College of Engg., Anantapur in the year 1991. Completed his M.Tech in Energy Systems in IPGSR of J.N.T.University Hyderabad in the year 1997. Obtained his doctoral degree from JNTU, INDIA