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Computation of Very Fast Transient over Voltages in ransformer by Wavelet Transform in 800KV GIS

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Abstract

In a GIS, Very Fast Transient Over voltages (VFTO) are generated mainly due to switching operations. The switching operation may be of a disconnect or switch or a circuit breaker or an earthing switch. These switching overvoltage levels are possible up to 3.0 p.u, depending on switching configuration .This paper deals with analysis of vftos in transformer, transformer model is considered and the vftos generated are analyzed by Wavelet.

***Keywords**: VFTO,,GIS,Transformer,Wavelet,Transients,DWT,*

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I. INTRODUCTION

This paper deals with analysis of VFTOs in transformer, in this work the transformer model is considered and the VFTOs generated is analyzed by Wavelet transforms then the result is compared between the two. Very fast transient over voltages (VFTOs) generated by operating disconnected in gas insulated switch gear (GIS) could cause dielectric and mechanical stresses and voltage oscillation inside the transformer connected. The situation is severer in the system that the main transformer is directly connected to GIS since the high frequency surges travel more easily along the coaxial gas insulated bus. The VFTOs in transformer windings have always been troublesome therefore it is important to analyze the wave both in time domain and frequency domain, therefore the wavelet transform is implemented. There are several works on vftos but this method is efficient and can be used to compute the effect of VFTOs in transformer .

II. THEORY OF WAVELET ANALYSIS

Wavelets are functions that satisfy certain requirements. The very name *wa6elet* comes from the requirement that they should integrate to zero, 'waving' above and below the *x*-axis. The diminutive connotation of *wa6elet* suggests the function has to be well localized. Other requirements are technical and needed mostly to insure 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 resolution 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.

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 implement able counterpart, the discrete wavelet transform (DWT). If the 'discrete' analysis is pursuing on the discrete time, the DWT is defined as

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

where, $s(n)$ is the signal to be analyzed and $g_{j,k}(n)$ 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

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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

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

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.

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.

A. 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.

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

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

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III. SCHEME OF EVALUATION OF VFOS

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

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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.

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 TRANSIENTS

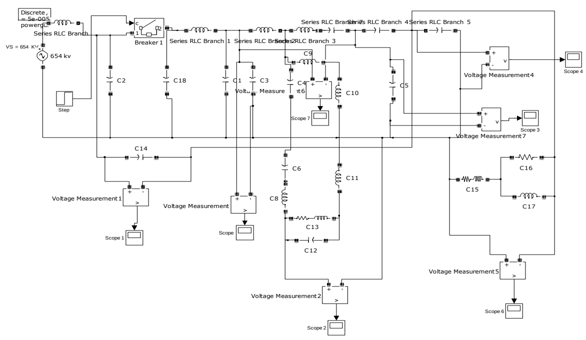

Fig 1 Matlab similink diagram oftransformer in 800KV GIS

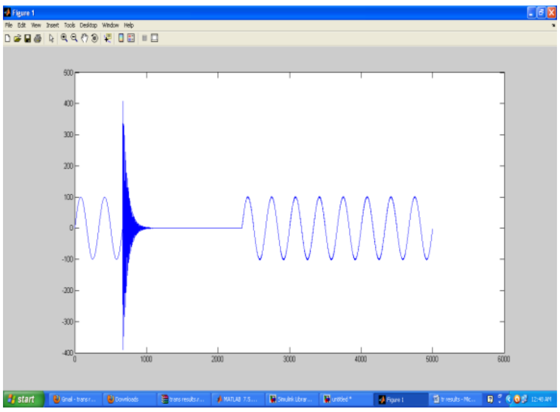

Fig 3 Vftos generated at the breaker contacts at open conditions

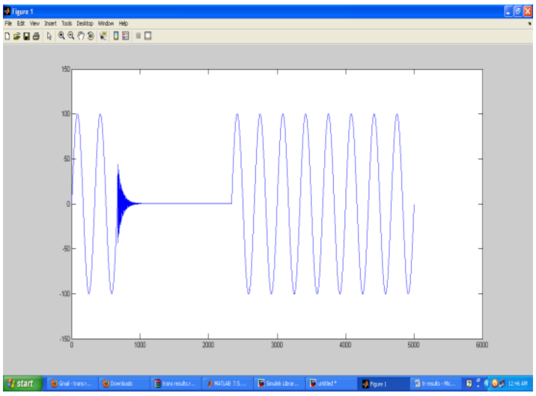

Fig 4 Vftos generated at the breaker contacts at closed conditions

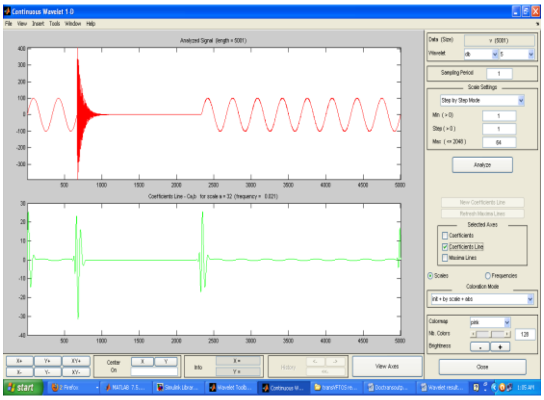

Fig5 Vftosby db4 wavelet transform at open conditions

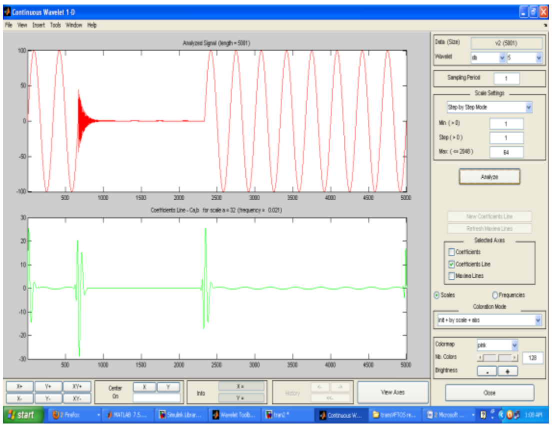

Fig6 Vftos by db4 wavelet transform at unclosed conditions

Measuring	Trapped charge			
	0Pu	.4Pu	.8Pu	1Pu
Vtr(Pu)	2.06	2.88	3.71	4.12
Voc(Pu)	2.36	3.68	4.74	5.26

Fig7 Vftos by db4 wavelet transform at open and closed conditions

V. CONCLUSION

In the present work , fault location is calculated and are shown in fig from 1 to 7 by using Continuous Wavelet Transform (CWT) using MATLAB simulation model. For all the faults under consideration with moving window algorithm, the error in the fault location is varied from - 10% to 13%. As the fault resistance in the fault increases the %error increases and the increase in %error is rapid at high fault resistances. As we are taking the impedance of the circuit during fault condition and healthy condition to calculate the distance where the fault has occurred, the %error in the distance measurement increases with the increase in fault resistance . If the fault resistance increases then resistance of the circuit under fault condition will be increased which may dominate the effect of reactance in that case and thus there may be some increase in %error. Tests including phase to ground faults and phase to phase faults and simulation results show that this CWT algorithm is identifying the fault from the instant at which faulted sample data enters the window and calculating the fault distance within half cycle after the fault inception. Identification of the frequency components in power system waveforms by using Mexican hat and Coif let as mother wavelet is also presented. The results of the present work will be useful in including innovative features in microprocessor based distance relays.

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BIOGRAPHIES AND PHOTOGRAPHS

BIOGRAPHIES OF AUTHORS

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2) D.Prabhavathi Born in 1976 august 27, her B.Tech degree from KSRM college of Engineering, kadapa, SV university, and M.Tech degree from SV iniversity in the year 2003.She has specialised in Power Systems, operation and control.She is currently working as Assoc.Prof ,dept of EEE Siddhartha Institute of Engineering and Technology, Ibrahimpatnam, Hyderabad Her research interests include Simulation studies on faults identification in UG cable of LT and HT. She has 12 years of experience.

3) Dr. M. Surya Kalavathi, Born on 8th July 1966, Obtained her B.Tech degree from S.V. U. in 1988 and M.Tech from S.V.U. in the year 1992. Obtained her doctoral degree from JNTU, Hyderabad and Post Doctoral from CMU, USA. She is presently the Professor (EEE) in JNTUH College of Engineering, Kukatpally, and Hyderabad. Published 16 Research Papers and presently guiding 5 Ph.D. Scholars. She has specialized in Power Systems, High Voltage Engineering and Control Systems. Her research interests include Simulation studies on Transients of different power systemequipment. She has 18 years of experience. She has invited for various lectures in institutes.

4)Dr.Bhumanapally.Ravindhranh Reddy, Born On 3rd September, 1969. Got His B.Tech In Electrical & Electronics Engineering From The J.N.T.U. College Ofengineeringanantapur In The Year 1991. Completed His M.Tech In Energy Systems In IPGSR Of J.N.T.University Hyderabad In The Year 1997. He Obtained His Doctoral Degree From JNTU, INDIA