MATLAB/Simulink STUDY AND IMPLEMETATION OF FAULT IDENTIFICATION OF EHV LINES USING WAVELET TRANSFORM BASED FLC

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ABSTRACT--*An appropriate method for fault identification and classification on extra high voltage transmission line using discrete wavelet transform is proposed in this work. The sharp variations of the generated short circuit transient signals which are recorded at the sending end of the transmission line are adopted to identify the fault. The threshold values involve fault classification and these are done on the basis of the multi resolution analysis. A comparative study of the performance is also presented for Discrete Fourier Transform (DFT) based Fuzzy Logic Controller (FLC) and DWT. The results prove that the proposed method is an effective and efficient one in obtaining the accurate result wit.hin short duration of time. Simulation of the power system is carried out MATLAB/Simulink*

Keywords--*Faulty, FLC, MATLAB, Wavelet.*

I. INTRODUCTION

In the transmission line short circuit fault occurs due to several reasons. It might be due to lightning strike, tree branches falling on transmission line, fog and many more. This may give raise to the consequence of permanent damage to the line insulators. So it has become necessary to analyze the fault on the transmission line in a better approach. The occurrence of any transmission line fault gives raise to a transient condition. The transient phase is marked by the presence of harmonic current. So far, several techniques are adopted for pattern recognition of generating the high frequency signals. ANN [2, 3] is used to identify and classify the faults. But the drawback of this method is the resolution is not efficient. Fourier Transform (FT) [4] is used in these schemes to process the original time domain signal but it may give raise to inaccurate spectra leading to frequency leaking and has poor time localized property for high frequency components of the signal. However, the problem of FT can be resolved b using Short Time Fourier Transform (STFT) [5, 6], which windows the input signal. As a single window is used for all frequencies, resolution of the STFT cannot vary for different frequencies. Many researches had been done using wavelet transform to analyze the performance of it. The wavelet transform provides a better detection when the signals changes abruptly [9], so it is praiseworthy for fault detection since the faulted signals changes abruptly. Wavelet transform is adopted to discriminate the faults type from the magnetizing inrush current [7] in the transformer and then wavelet transform is used for fault identification and classification [10]. Multiresolution capability is advanced technique of wavelet transform which makes windows automatically and identifies and

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classifies the faults for the different signals [11], but the threshold values implemented for fault detection is not mentioned. By considering the above mentioned method, faults are classified [12] but fault impedance and fault inception angle are not taken into consideration. The same wavelet approach is also used to classify faults in the underground cable system [1]. Moreover the wavelet transform gives result closely related to IEC (International Electro technical Commission) standard framework [14] for harmonic analysis in power system. The proposed analysis involves the multiresolution method, where the threshold values are employed to identify and classify faults. In this approach DFT limitations are overcome by wavelet transform method which uses short windows for high frequencies and long windows for low frequencies.

II. IMPLEMENTATION OF DESIGNED MODEL

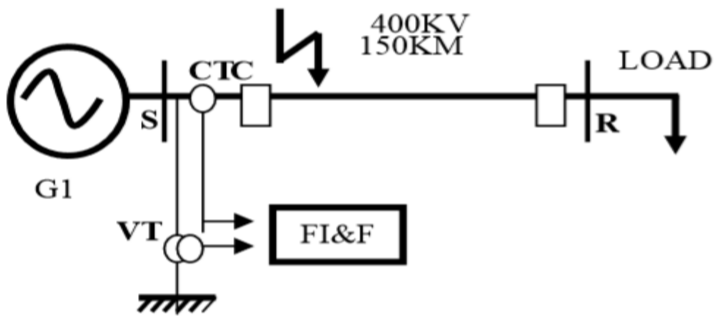

Figure 1: Power system under study

The simulations were done on a simple transmission line circuit consisting of a generator at one end and a load at the other end and the line is extended to 150 km without mutual coupling. The base value of the voltage in the system is 400kV. The frequency of the system is 50Hz. Simulation of the simple power system is done using MATLAB. Fig.1 [3] shows the power system under study, in which FI and FC denotes Fault Identification and Fault Classification respectively. The transmission line is represented by lumped parameters (3 Pi sections are used) and its parameters frequency dependence is taken into consideration without mutual coupling [17].

This method is not based on the amplitude of the voltage transient but on the frequency found in the transients. This is the major advantage of this method. This method was tested with four different values of internal impedance of the generator and the load models taken for the test are, in case 1, source resistance is 0.5ohm and source inductance is 10e-3. In case 2, source resistance is 0.89 ohm and source inductance is 16.58e-3. In case 3, source resistance is 1 ohm and source inductance is 30e-3. In case 4, source resistance is 2 ohm and source inductance is 60e-3 with fault points (distance of the fault) taken for test were 10, 20, 30, 40, 50, …….120km. The different values of fault resistance were 5, 10, 20 ohms. Fig. 2 shows the proposed method’s functional block diagram. The voltage and current waveforms of the simulated power system are fed as input to the sampling network. The signals are sampled at 50 KHz [5] to obtain higher resolution. The sampled signals are given to the discrete wavelet transform to identify and classify the faults. Thus different types of faults are classified. The proposed method is also applicable to a double-circuit untransposed line.

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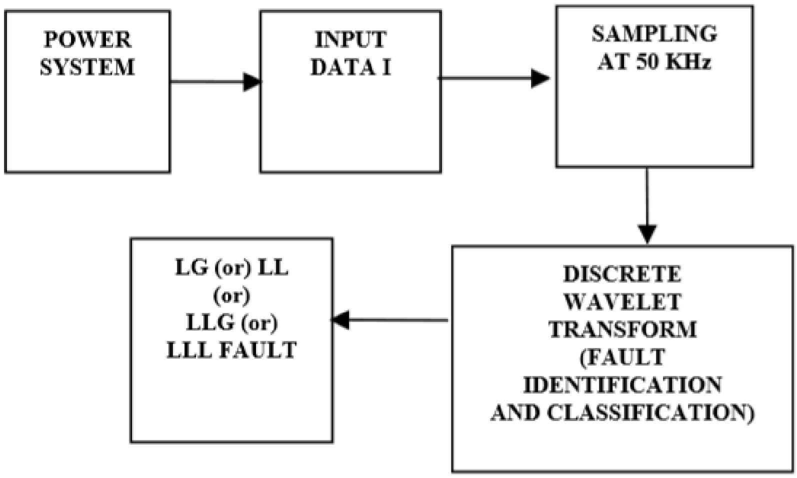

Figure 2: Function block diagram of DWT method

III. WAVELET TRANSFORM

A wavelet is an oscillatory waveform of effectively limited duration that has an average value of zero, waving above and below x-axis. In particular, the wavelet transform is of interest for the analysis of non-stationary signals which does not change periodically with time. Wavelet are functions that satisfy the requirements of both time and frequency localization. In this paper the discrete wavelet transform is adopted in which the wavelets are orthogonal to each other.

The DWT in terms of ψm, n can be represented as

$$X_{m,n} = \sum_{k=1}^{n+1} x(k)\, \psi_{m,n}(k) \tag{1}$$

The signal x (t) can be represented by its DWT coefficients as:

$$x(t) = \sum_{n=-\infty}^{\infty} \sum_{m=-\infty}^{\infty} X_{m,n}\, \psi_{m,n}(t) \tag{2}$$

Where, k = discrete variable, n, m = scaling variables, ψ = scaled and shifted versions of the wavelet function. Wavelet transform uses short windows for high frequencies and long windows for low frequencies in contrast to STFT which uses a single analysis windows i.e. window length cannot be varied. Thus the frequency resolution is constant and depends on the width of the chosen window. But, frequency resolution can be varied for desired requirements in DWT as it has multiresolution capability which can be seen from the following theories.

IV. MULTIRESOLUTION WAVELET ANALYSIS (MRA)

The MRA is the new and powerful method of signal analysis well suited to fault generated signals. In MRA, the original signal is decomposed into 'scales' using wavelet prototype function called "mother wavelet" while frequency analysis is performed with a low frequency version of the mother wavelet and temporal analysis is performed with a high frequency version of the mother wavelet. Let x[n] be the discrete time signal, n is the samples. This signal is decomposed into c1[n] and d1[n] at scale 1, where c1[n] is the smoothed version of the original signal and d1[n] is the detailed version of the original signal. These are given by

$$c_1[n] = \sum_{k=1}^{n+1} h[k-2n]\, x\,[k] \tag{3}$$

$$d_1[n] = \sum_{k=1}^{n+1} g[k-2n]\, x\,[k] \tag{4}$$

Here h[n] and g[n] are the associated filter coefficients that decompose x[n] to c1[n] and d1[n] respectively. The next higher scale decomposition will be on c1 [n].Thus at scale 2, c1[n] is decomposed to c2[n] and d2[n] and so on. Thus the decomposition process can be iterated, with successive approximate being decomposed in turn, so that the original signal is broken down into much lower resolution compact, d1[n] is used for threshold checking to estimate the change time-instants. The change time-instants can be estimated by the instants when the wavelet coefficients exceed a given threshold value. The detailed version only involves the fault identification and classification, which necessitate a smoothed version. The smoothed version is got by the following smoothing operations: (a) It removes confusing multiple close-spikes and combines them into single unit impulse. (b) It removes unwanted glitches, which can otherwise result in false positives for the abrupt changes. (c) The segments in the power system fault analysis are during the pre-fault condition and the following events like fault initiation, circuit-breaker opening and reclosing. These events are predefined and are the number of segments. So, any bigger number of segmentation possibly indicates transients, power swings and the like. Estimation of the number of segment(s) is also performed and checked to distinguish the fault from the transients, power swings, etc. (d) Based on the modeling of the segments, analysis is done for estimating the event-critical change instants, rejecting others. Thus, MRA provides a more efficient way of representing a signal at different resolution scales.

V. FAULT IDENTIFICATION USING MRA

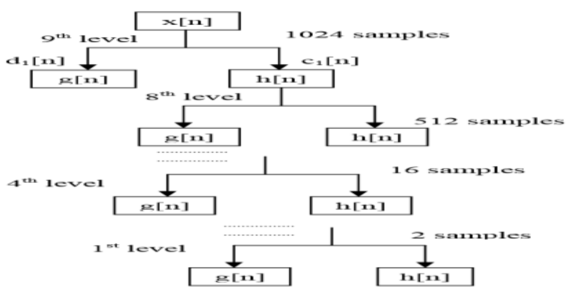

Figure 3: Filter bank model implementation for MRA

The fault is identified and classified using the faulted features extracted from the harmonics with the aid of MRA approach. The important parameter in the wavelet analysis is the wavelet type. After examination of several kinds of wavelet, the Daubechies-D4 wavelet [8, 11] is proved to have little computations burden and it is suitable for both low and high frequency analysis.

VI. FLC

Fuzzy logic Controller (FLC) in multi source multi area Hydro Thermal system is shown in fig 4. it is used to analyze the faulty signals through inputs and output of EHV lines voltage (Refer Figs. 5 to 7). The weighted average method is used for defuzzifiation.

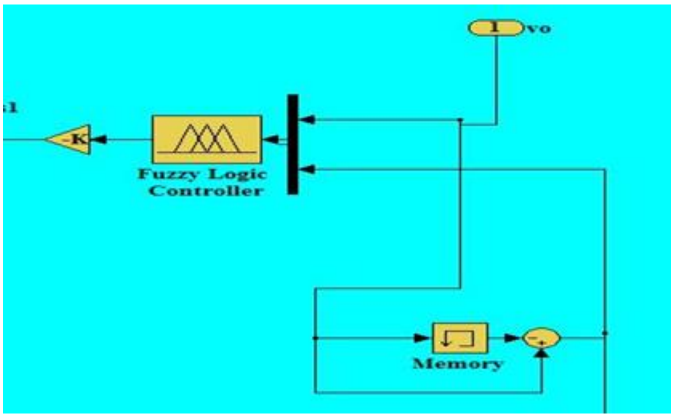

Figure 4: Configuration of PDIC and FLC

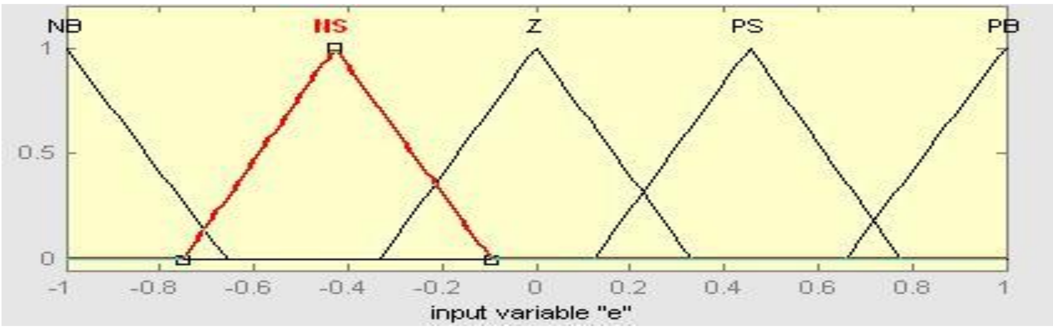

Figure 5: Membership's functions of FLC - error

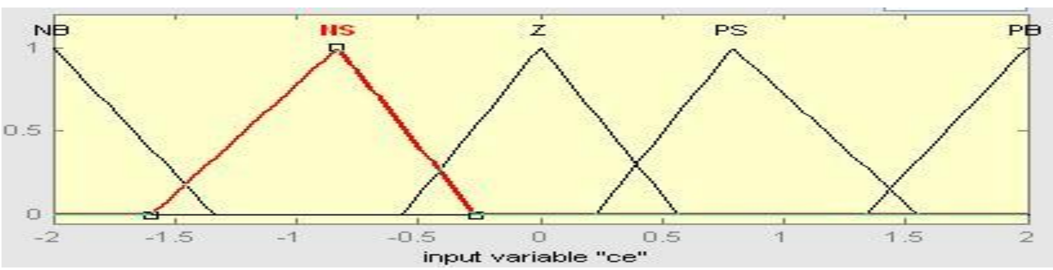

Figure 6: Membership's functions of FLC - Change in error

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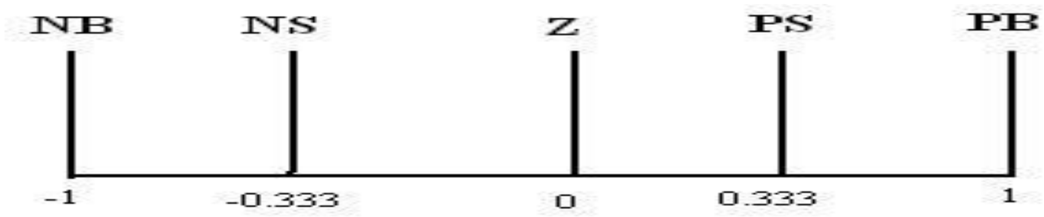

Figure 7: Membership's functions of FLC- output (o)

VII. SIMULATION RESULTS

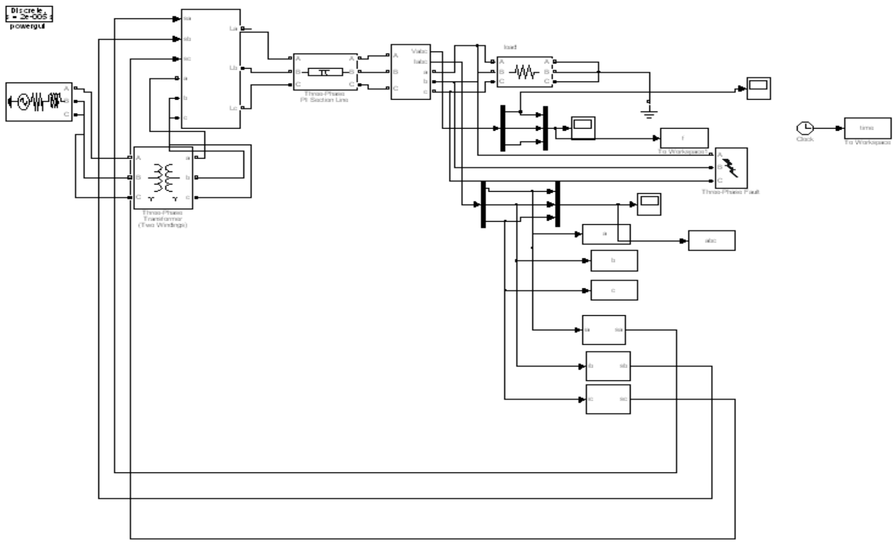

Figure 8: MATLAB/Simulink model of test system

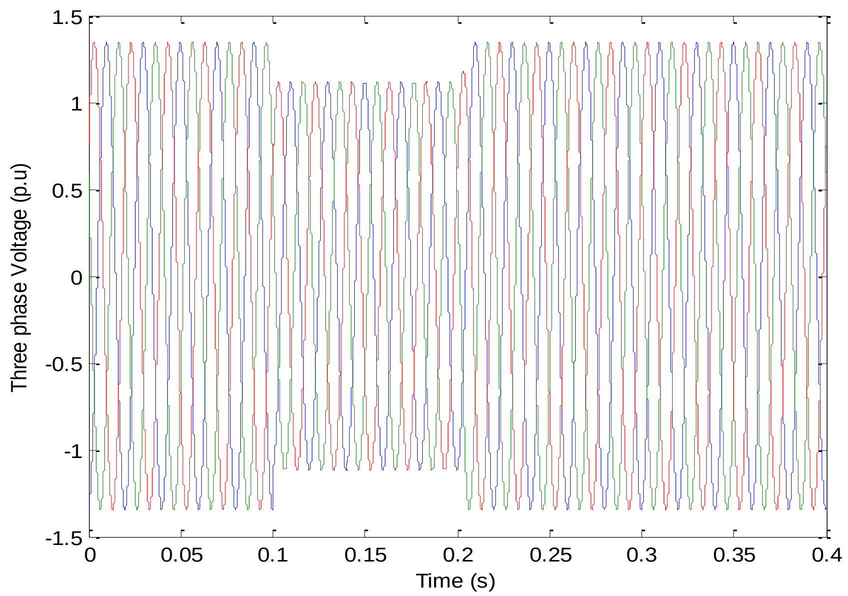

Figure 9: Simulated p.u three phase load voltage during faulty conditions

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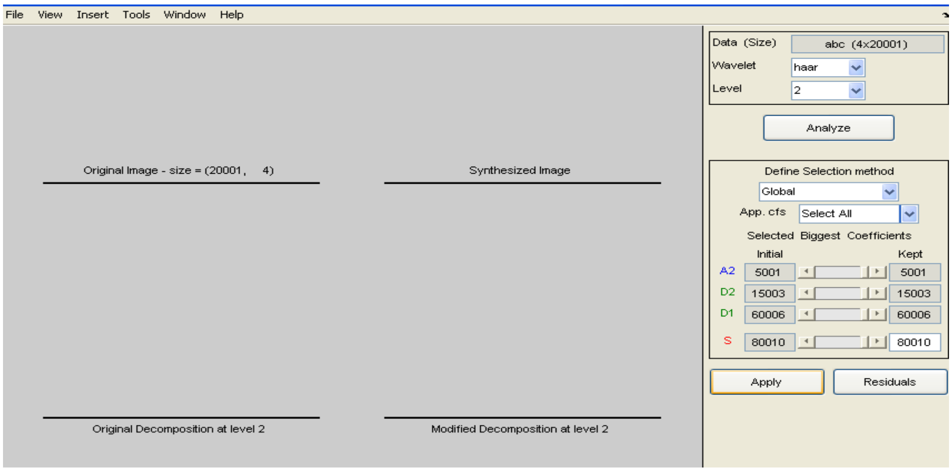

Figure 10: Selected coefficient of the faulty signal using wavelet based FLC

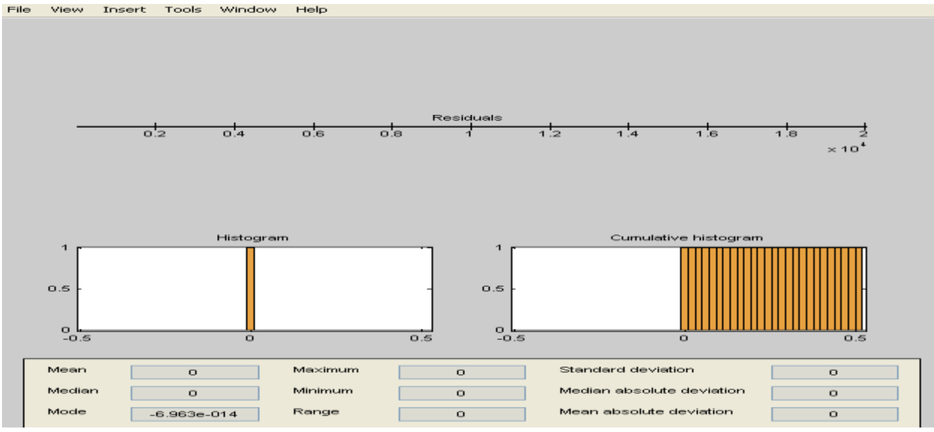

Figure 11: Residuals analyses of the faulty signal using wavelet based FLC

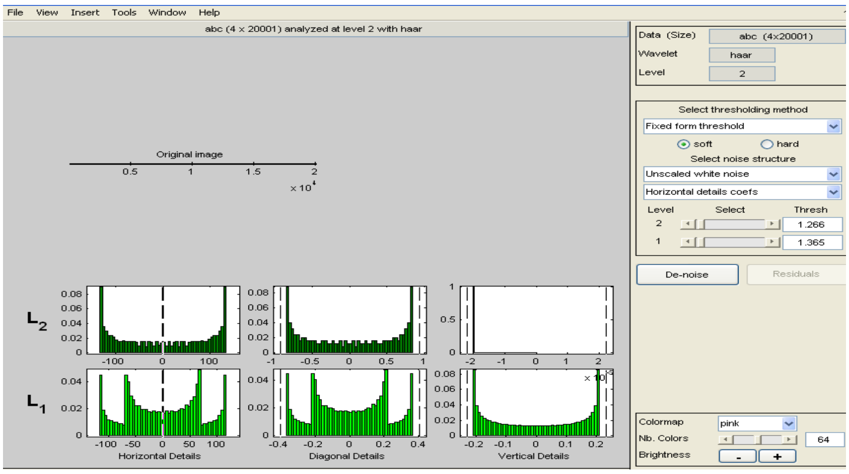

Figure 12: De-noise analyses of the faulty signal using wavelet based FLC

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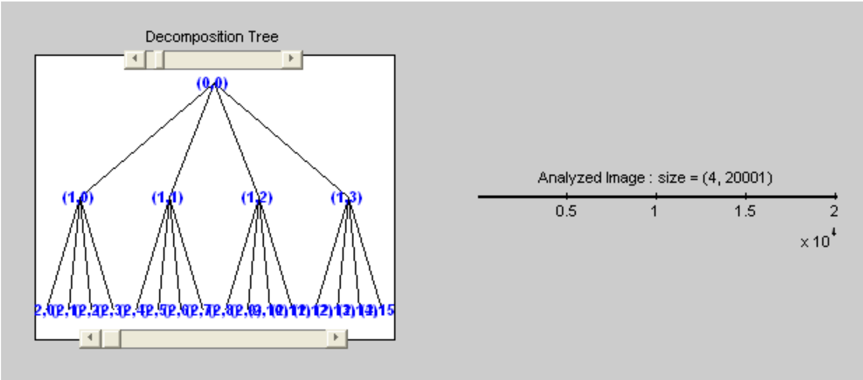

Figure 13: Decomposition tree analysis of faulty signal using wavelet based FLC

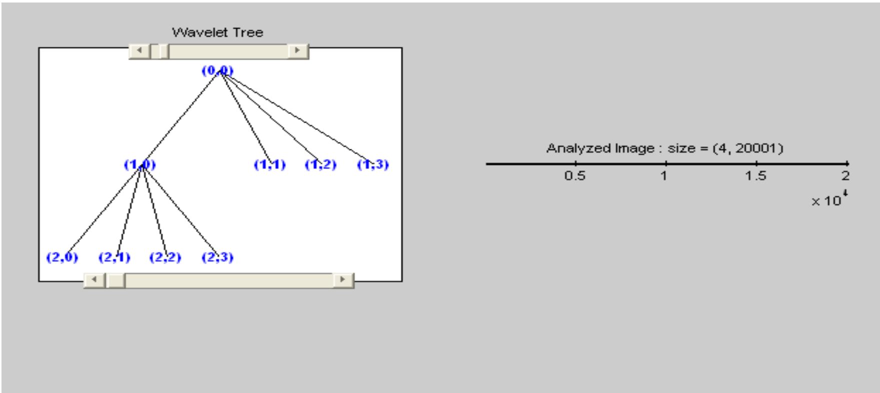

Figure 14: Wavelet tree analysis of faulty signal using wavelet based FLC

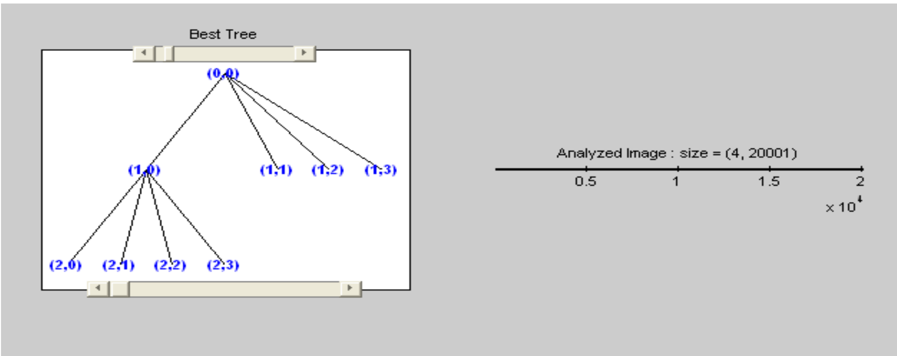

Figure 15: Best tree analysis of faulty signal using wavelet based FLC

From fig. 8 to 15 shows the simulated responses of faulty signals using wavelet transform based FLC. To predict the faulty.

VIII. CONCLUSIONS

Implementation of Fault Identification of EHV Lines Using Wavelet Transform Based FLC has been successfully completed through the computer simulation using MATLAB/Simulink. Three phases faulty is applied and analyzed using wavelet transform based FLC. Many simulation results are presented to show the proficient of the designed model.

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