High Impedance Fault Detection in Electrical Power Feeder by Wavelet and GNN

Majid Jamil, Rajveer Singh and S. K. Sharma

Abstract— **The distribution feeder faults need to be detected and isolated in a reliable and accurate manner, for maintaining the efficient and reliable operation of distribution electrical power systems. A number of techniques are available for detecting and classifying the fault. However, the results are not satisfactory in case of high impedance fault (HIF) occurs on distribution feeder due to very low value of fault current. Keeping in view of aforesaid situation, a new approach based on generalized neural network (GNN) and wavelet transform is presented here for HIF detection. Wavelet transform is used to obtained the information from the measured faulty current in terms of standard deviation of wavelet coefficients. The obtained features are then used as an input to the GNN model for the detection of HIF on a given distribution feeder. The values obtained from GNN algorithm are compared with ANN and well established mathematical models and are found more accurate. All the calculations are done in Simulink/MATLAB®.**

***Index Terms*— HIF, Wavelet, GNN, Electrical Fault, Power Distribution.**

I. INTRODUCTION

An electrical power system deals with number of sub stations, which are of different kinds, which are interconnected by number of tie line systems, by transmission lines, by sub-transmission lines and various others distribution systems to supply electricity to the different kinds of load and different consumers. The electrical power distribution system is very important part of an electric power system, which supplies electric energy to the end user and immediately affects the consumers. Electrical power distribution systems are responsible for maintaining the uninterrupted the power supply to the geographical dispersed residential, commercial and industrial customers in a safe, reliable and economical environment. But electric power systems are daily exposed to service interruption due to fault which causes reduction in power quality. To overcome such problems conventional protection schemes have been used. The conventional protection schemes able to detect and protect LIF, but fail in case of HIF because of very low value of fault currents.

HIF is a great concern of matter to the power engineers and is reported in the literature by researchers. The detection of HIF is very difficult and
Power System Relaying Committee (PSRC) working group indicates that the success rate is near about only 20% by using conventional protection schemes and generally occurs at voltage levels of 15 kV and below [1]. If HIF goes undetected they are hazardous to the human being as they leave an live conductor exposed and uncleared. Saving personnel and properties from damage or injury caused by such faults is first priority of utilities. Although several detection methodology have been proposed so far, but an efficient, secure and reliable HIF detection methodology is objectives of the continuous research.

Initially the detection of HIF involved the straight measurement of primary electrical quantities/parameters, i.e. three phase voltages and currents and by analyzing in the their variations or by analyzing their harmonic components. The various methods developed which employed the various combinations of above said parameters [2-8]. But the results are ambiguous because of the similarity of information between frequency domain data produced by high impedance faults and other transient events occur on electrical power system, which leads to mal operation of protection system. Thus, it is very difficult to find out useful information from one or more critical boundaries line harmonic components that can differentiate the HIF from the disturbance of transient nature.

The signal processing studies on current signals, considering each and every possible power system situation, can be used to the develop algorithms, which are based upon frequency and time domain and this highly improves the HIFs detection capacity in electrical distribution feeder systems. Instead of analyzing time domain and frequency domain information, the hybrid analysis of low frequencies and high frequencies can be achieved by the de-composition of the measured current signal by using WT. The HIF detection based on ANN have been carried out by many research fellows, but this methodology is unable to discriminate HIF and capacitor switching. Therefore, Ibrahem Baqui et al, presented a methodology based on WT and ANN to take the advantages of both the tools [15].

Even though WT-ANN based method has been quite successful in detecting the types of fault, but the method is not free from disadvantages of ANN i.e. more duration of training, requirement of large training data set, problem of assuming weights, comparatively requirement of more number of hidden layers etc. These problems of ANN have been overcome and to improve the training performance of Artificial Neural Network and to improve the performance of testing, a new approach which is based on GNN in combination with WT is presented in this paper. The uses of GNN in the field of electrical power system electrical load calculations, power system stabilizer, estimation of solar energy etc. are available in the literature [9–14].

This paper is classified as follows: Wavelet transform

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used for feature extraction of faulted current signals in terms of statistical feature i.e. standard deviation is presented in Section 2. Section 3 presents the generalized neural networks and HIF detection based on GNN model. Section no. 4 describes the simulation studies. In Section no. 5 results are discussed. Section 6 presents conclusion.

II. Wavelet Transform

The time-frequency information from the transient signal wavelet transform is a better choice for the analysis of electrical power system transient phenomena. Wavelet transform (WT) divides a signal into different frequency bands by using translation feature *i.e.* shift in time and by dilation *i.e.* compression or de-compression with respect to time of a predefined fixed wavelet function of zero average value, known as mother wavelet. The and multi resolution analysis of signal by discrete wavelet transform provides a short window for high frequency components and long window for low frequency components, this leads to an fine time resolution as well as fine frequency resolution, which is helpful in transient analysis.

In Mathematics, a continuous wavelet transform (CWT) is used to divide a continuous-time function into Wavelet. Unlike Fourier Transform, the continuous wavelet transform possesses the ability to construct a time frequency representation of a signal that offers very good time and frequency localization given below as:

$$X(c,d)=\frac{1}{\sqrt{|c|}}\int_{-\infty}^{\infty} f(t)\psi(\frac{t-d}{c})dt \qquad (1)$$

where c is the dilation or scale constant and d is the translation constant . The c and d both variables are continuous in narure. It is understood from equation (1) that the original signal *f(t),* which is in domain and is one-dimensional is decomposed into to a new two-dimensional signal across scale constant c and translation constant d.

In DWT, a time-scale representation of the digital signal is obtained using digital filtering techniques. The signal to be analyzed is passed through filters with different cutoff frequencies at different scales. Mathematically, the DWT of a given signal $f(t)$ with respect to a mother wavelet $\psi(t)$ is defined as:

$$DWT(m,k)=\frac{1}{\sqrt{a_0^m}}\sum_n f(t)\psi(\frac{k-nb_0a_0{}^m}{a_0^m}) \qquad (2)$$

where ψ (.) is the mother wavelet and the scaling and translation parameters a and b are member of an integer for parameter m, i.e. c = $a_0{}^m$ and d = $nb_0a_0{}^m$, they produce a new group of dilated mother wavelets, known as daughter wavelets, these basically depends upon mother wavelet. In the equation (2), the k is a variable integer by nature that refers to a specific number of samples in an input wavelet signals.

2.1 Multi-resolution analysis

Multi-resolution analysis (MRA) is an effective signal processing tool in monitoring and analyzing power system perturbation. The signal to be analyzed is split into different frequency level and statistical values (mean, mode, median, variance, standard deviation, etc.) for each frequency level are noted. MRA provide a substantial amount of data reduction because of down sampling at each level and it have a simple and fast algorithm. Therefore, DWT is most appropriate for fault detection and location problems in power systems. In this paper phase A, phase B and phase C fault currents, generated on a three phase distribution feeders considered as X(n) in time domain is passed through high pass H(n) and low pass filter G(n) simultaneously. The outputs from both the filters are down sampled by a factor of two to obtain the detail coefficient represented by (cD1) and the approximation coefficient represented by (cA1) which constitutes the level one decomposition of the input original signal at stage first. The approximation coefficient (cA1) is then again passed to the second stage to repeat the above procedure. Finally, the signal is decomposed up to the seven levels. The details information and approximations at different levels are seen to provide useful clues regarding the faults detection on the distribution feeder. A multi-level DWT decomposition scheme shown in Fig. 1. The approximations and details from level-1 to level-7 have been represented using suffixes 1, 2, . . . and 7.

2.2. Features Extraction

Three phase current signals recorded at substation are sampled at the rate of 512 sample per cycle. These sampled data are passing through seven level wavelet filter bank, selecting Db4 as mother wavelet, to obtain useful signature for different transient conditions using MATLAB software. The useful signature of current signals is captured by calculating statistical feature for each frequency band. In this paper, standard deviation (STD) is considered as a statistical feature for feature extraction of signals. STD of coefficients for each frequency band is calculated using equation (3).

$$STD=\sqrt{(\frac{1}{n-1}\sum_{i=1}^{n}(x_i-\bar{x})^2)} \qquad (3)$$

where 'x_i' is i^{th} sample of wavelet coefficient, ' $\bar{X}$ ' is average of the detail coefficients and 'n' is the the number of samples of wavelet coefficient. The obtained STDs of the coefficients, for each frequency band, are then collected in the matrix form and are utilizes this matrix vector as the input data vector to a GNN.

III. Architecture Of A Generalized neural Network

The generalized architecture of a simple neuron has an aggregation function, which is followed by an activation function. The complete structure is shown in Fig. 2, whereas in generalized neural model both summations as well as product is taken as aggregation function. The outputs of these aggregation functions passes through Sigmoid and Gaussian functions respectively as shown in Fig. 3.

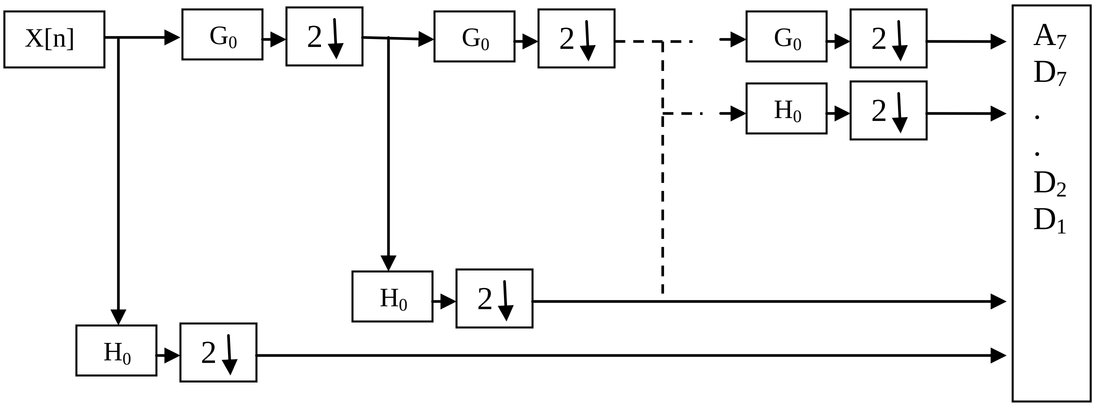

Fig. 1. Seven level wavelet filter bank

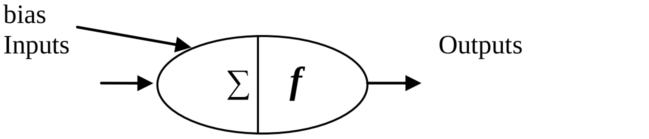

Fig. 2: Structure of a simple neuron

The output of the summation part *i.e.* ∑ with a Sigmoidal characteristic function of the generalised neuron is

$s\_net = \sum W_{\Sigma i} X_i + X_{o\Sigma}$ and λs is the gain scale factor of Σ_1.

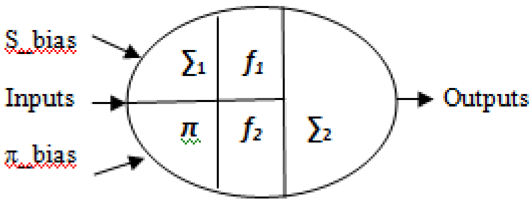

Fig. 3: A typical GNN model

The output of the π part with Gaussian characteristics function of GNN is

$$O_{\Pi} = f_2(pi\_net) = e^{-\lambda p * pi\_net^2} \qquad (4)$$

where

$pi\_net = \prod W_{\Pi i} X_i * X_{o\Pi}$ and λp is the gain scale factor of Π.

The final output of the neuron basically is a function of the two outputs. *i.e* O_{Σ} and O_{π}. The weights W and (1-W), are also plays important role respectively, and are represented as:

$$O_{pk} = O_{\Pi} * (1 - W) + O_{\Sigma} * W \qquad (5)$$

The generalised neuron provides only single output. If we have a system, which requires more than single output, then one generalised neuron is required for each required output [10]. The learning algorithm present in [10] has been used for updating weights of GNN to reduce error less than error-tolerance.

IV. Simulation Studies

The three phase currents are obtained from the power system model, by simulating under various combinations of operating conditions, which can occur in a practical power system. The actual electrical distribution power system model is developed in the Simpower system tool box of the MATLAB. The model is simulated by taking different values of the various parameters of the power system, which are supposed to vary in practical operation. The obtained signals are analysed by DWT and the STD is obtained to prepare the input data set for GNN. The proposed fault detection approach is extensively tested on 11 kV, 50 Hz distribution Khidgaon feeder line of 20.97 km length, connected with Gandhawa sub-station as shown in Fig. 4. HIF model used for HIF study is also shown in fig.5.

The model of a real time distribution feeder system has been tested and verified with real time data, obtained from a the electrical distribution company Power Research and Development Consultants Pvt. Ltd., Karnataka, India. In simulation studies, a large numbers of test cases are generated for different values of fault resistance (R_f) varying from 1 Ω to 10 Ω for LIF and for HIF from 300 Ω to 1000 Ω. Fault inception angle is varied from 0° to 90° with an interval of 18°. The capacitor switching is also considered in the substation bus bar and its values is varied from 5 kVAR to 30 kVA at 0.02 second of inception time. The combination of the various output layer neurons of developed model identifies the exact feeder situation, is shown in Table 1.

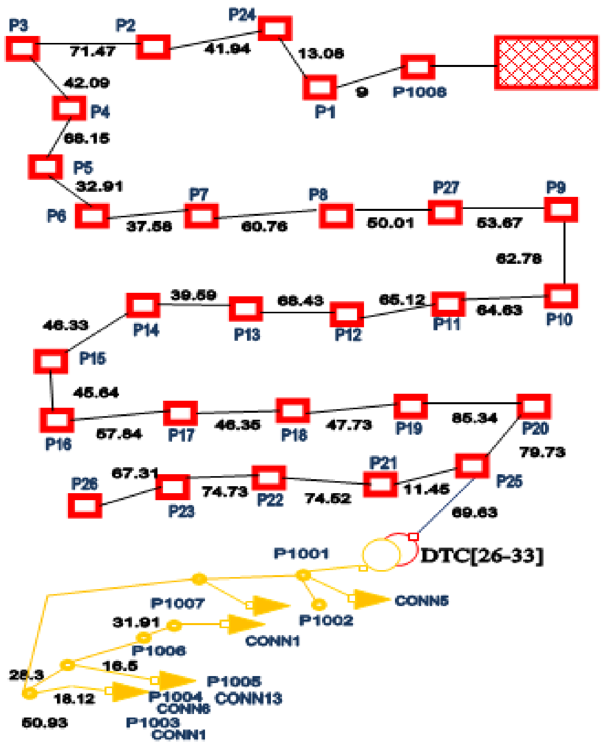

Fig. 4: Single line diagram of 11 kV Khidgaon (MP, India) feeder

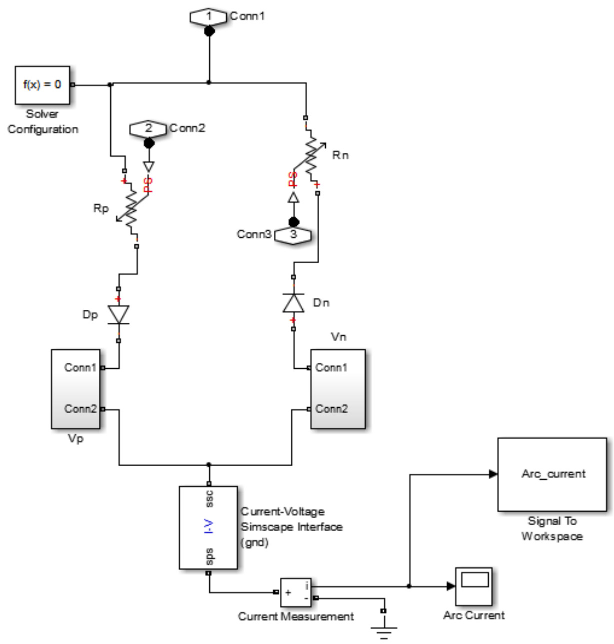

Fig. 5: HIF Simulink model

Table 1: ANN targets

Output Neuron	HIF	LIF	Normal
1	1	0	0
2	0	1	0
3	0	0	1

V. Results

The process of HIF detection starts by application of DWT to the measured current signals (Ia, Ib, and, Ic of respective three phases). After calculating the detailed coefficients of signals the STD from all levels of frequency bands are calculated. These values are normalized and then used as the inputs to GNN. The condition of a distribution feeder under test is obtained according to the required outputs provided by the developed NN. The overall performance of the proposed method has been checked again and again by its application to distributed system and obtained input data vector under various operating situations/contingencies.

A. Results of High Impedance Fault Condition

The nature of the faulty phase current (I_C) is not consistent, but changes in haphazard manner. The waveform of decomposed faulty phase current (I_C) signal of under a HIF is obtained and is shown in Fig.6. The dominant Wavelet levels (having high values of normalized STD) are a_7, d_7, and d_6, which represent the 50 Hz fundamental power frequency components and other lower harmonic frequency components which are included in the fault current. The high frequency transients generally appear during the arc period (from the appearing of arc to the extinction of the arc) and which are present in the decomposed Wavelet levels d_1 to d_4. The normalized standard deviation value of each decomposition level, which has been obtained from the analyzed signal, is shown in Table 2. The output of the GNN to this input data matrix, the output of is [1 0 0]' which is corresponds to HIF.

B. Results of Low Impedance Fault Condition

The Fig. 7 shows the result of discrete wavelet analysis of the measure current signal which is obtained by SWT. The Peaks occurs in the beginning of wavelet decomposition levels and at the end of the edges in wavelet decomposition levels, *i.e.* from d_1 to d_4. The normalized STD value of each decomposition level that has been calculated from analyzed current signal is shown in Table 3. Using these data as the input of GNN, the output of GNN is [0 1 0]' that is LIF.

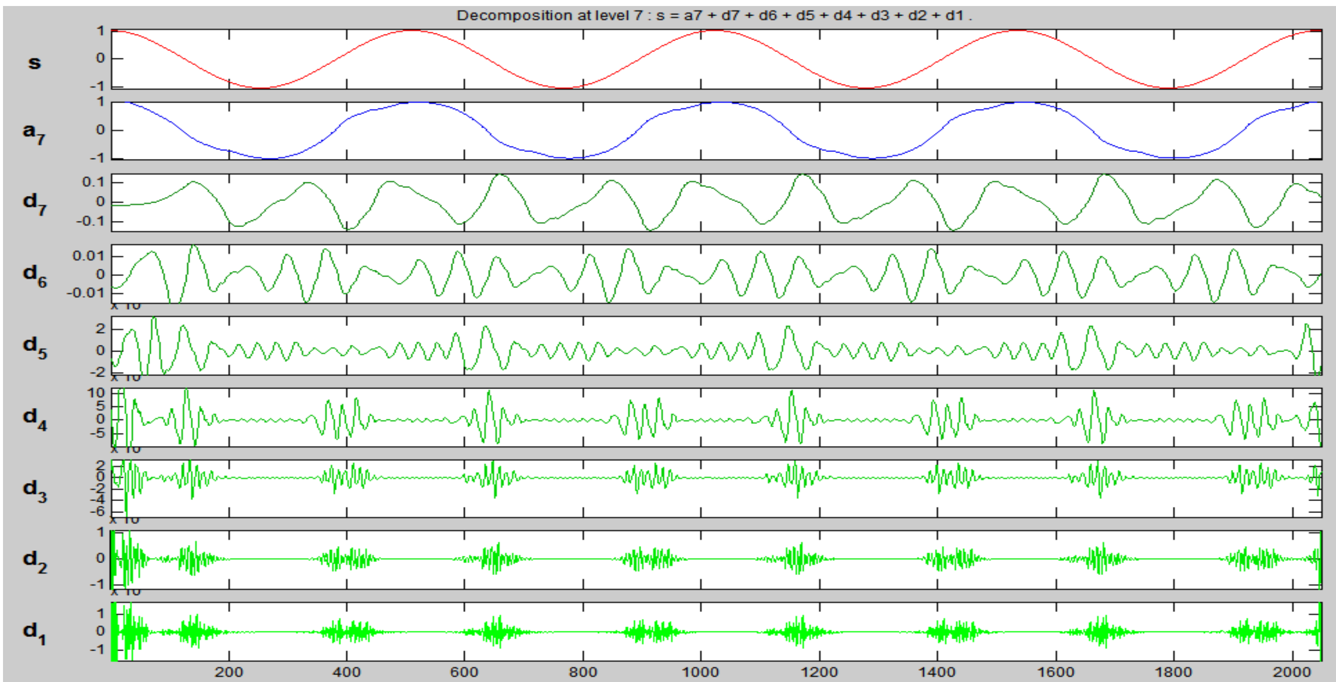

Fig. 6: Discrete Wavelet Transform of the phase current I_C under HIF condition

Table 2: Normalized STD values of phase current I_C under HIF condition

Decomposition level	Phase A	Phase B	Phase C
d1	0.000508000	0.000508830	0.000548456
d2	0.000629527	0.000562178	0.000565533
d3	0.001496230	0.001317130	0.000695792
d4	0.002372683	0.002654622	0.001578802
d5	0.013552138	0.015724094	0.013932614
d6	0.153671753	0.153114661	0.135549085
d7	0.427261405	0.457904928	0.454869854
a7	0.216065116	0.253211638	0.473270276

Table 3: Normalised STD values of phase current I_C under LIF condition

Decomposition level	Phase A	Phase B	Phase C
d1	1.04000E-05	0.89200E-05	0.000253538
d2	0.000110517	0.000102969	0.000611295
d3	0.000499885	0.000452321	0.000433876
d4	0.000970885	0.000899544	0.004701118
d5	0.005661291	0.004911554	0.031985763
d6	0.058195299	0.045927063	0.254199721
d7	0.163277652	0.133116297	0.834473274
a7	0.070485218	0.085169950	0.419326870

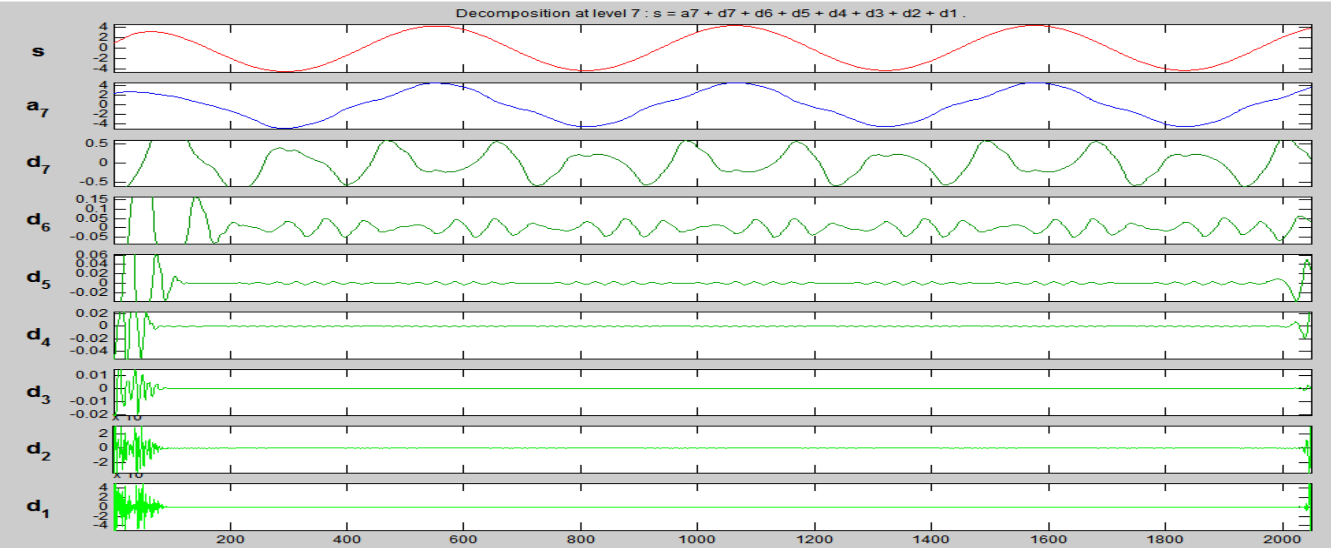

Fig. 7: Discrete Wavelet Transform of the phase current I_C under LIF condition

C. Results under Normal Condition

The behaviour of the phase current Ic (decomposed signals) of under a capacitor switching is shown in Fig. 8. The variable nature of current i.e. increasing or decreasing does not affects the output results obtained by the proposed method. The results are unfazed because that the high impedance arc duration time is very less so the part of high frequency signal only occurs appears for a very short duration of time period *i.e.* at the time of switching of the capacitor. Normalised STD value of each decomposition level that has been obtained from the analyzed signal is shown in Table 4. Using these data as the input of GNN, the output of GNN is [0 0 1]' that is normal state.

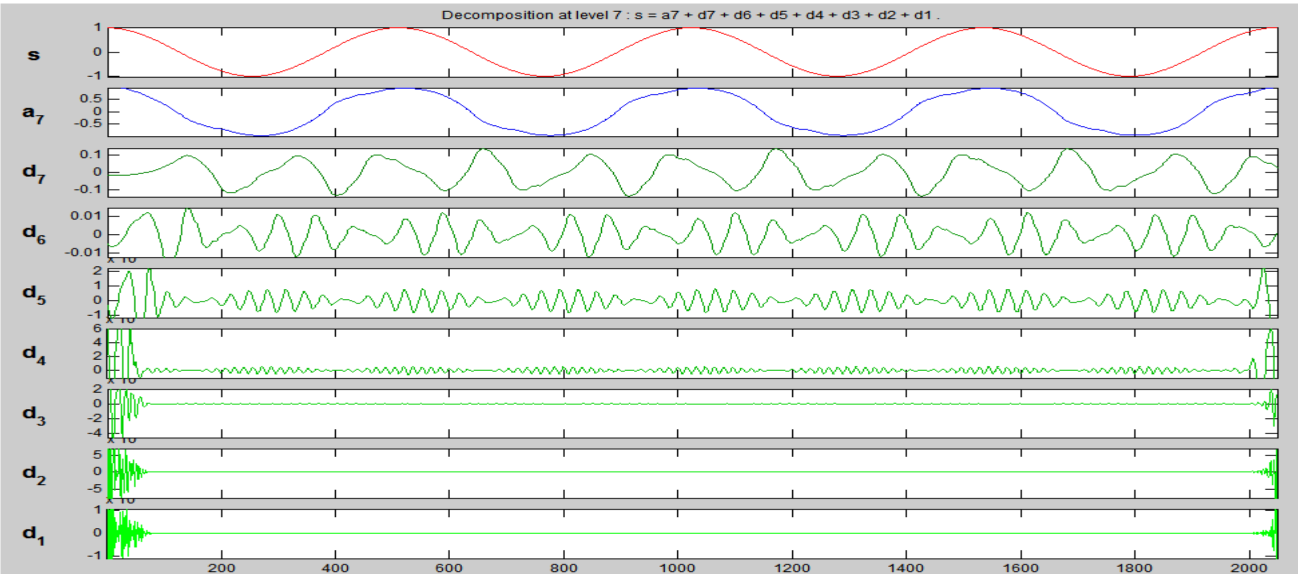

Table 4: Normalised STD values of phase current I_C under normal condition

Decomposition level	Phase A	Phase B	Phase C
d1	0.000704564	0.000461436	0.001183031
d2	0.000496871	0.000274049	0.000437295
d3	0.002108996	0.001546079	0.000822501
d4	0.004467236	0.002939623	0.002821163
d5	0.016356163	0.015797987	0.013415601
d6	0.146982107	0.151138785	0.122160590
d7	0.410552476	0.431202008	0.404583642
a7	0.248521446	0.295751400	0.521994363

VI. Conclusion

In the proposed study a GNN based fault detection technique on a real distribution feeder is presented. The fault current signals of the three phase feeder are filtered through wavelet transform the fault current signals are obtained at sampling frequency of 25.6 Hz. MRA based on dwt is used to analyse the transient characteristics of the phase current signals the information obtained in each frequency band by wavelet transform and the standard deviation of coefficients is fed as input to the GNN. The validation of the proposed approach is done by applying a very large number of test cases generated for different fault conditions. It is found that the proposed GNN model performance is better than other methods. As GNN requires less data to analyse, there for the time taken for detecting HIF is quite less. The scheme can be extended to real time production of power system.

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