

Discrete Wavelet Transform And Adaptive Neuro Fuzzy Inference System-Based High Impedance Fault Detection And Classification On 11KV/ 0.415 KV Power Distribution Network

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Abstract— In this paper, the Discrete Wavelet Transform and Adaptive Neuro Fuzzy Inference System-Based High Impedance Fault (HIF) Detection and Classification on 11KV/ 0.415 KV power distribution network (PDN) is presented. The case study PDN is located in Eket town in Akwa Ibom State Nigeria and it has a total of six 11 kV/ 0.415 kV power substations and one 33/11kV power injection substation. Daubechies wavelet (dB5) is employed in the DWT fault analysis. The root mean square (RMS) values of each phase current (feature extracted by DWT) serves as the inputs to the ANFIS model for HIF detection and classification. The ANFIS-based HIF detection model has three inputs (PhA_rms, PhB_rms and PhC_rms) and an output (FD). The values of the RMS of the d1 detail components of phases A, B and C of the PDN line under consideration are the inputs to the ANFIS model, while the outputs are binary values that indicates the state of the PDN line (i.e. 0 – no fault, 0 – shunt faults and 1 – High impedance fault). MATLAB / SIMULINK environment was used for the development and simulations of the case study distribution network and DWT-ANFIS models. In all, the results show that the HIF detection and classification were very effective and were achieved with a very low RMS value of current and with 99.78 % accuracy.

Keywords— Discrete Wavelet Transform, Power Distribution Network, Adaptive Neuro Fuzzy Inference System, Transmission Line , High Impedance Fault

1. INTRODUCTION

Over the years, in the electric power industry, safety has been identified as one of the most essential requirement in power distribution networks and failure to ensure safety in such power networks has in most cases resulted in sever damages to human lives and equipment's [1,2]. Faults in one of the major sources of dangers in power network and incidence of High Impedance Faults (HIF) in many cases results in death and untold financial losses. Notably, HIF occurs when live conductors are making contact with the ground or with high impedance material and this results in low currents [3,4]. With the low current, the usual over current relay, it is not possible to detect this kind of fault and it is treated as a normal load current rise [5].

Two forms of HIF have been identified, one form occurs when live broken conductors makes contact with surfaces that have high impedance such as grass surface or surface covered with asphalt [6]. A second form of HIF occurs when live conductor (that are not broken or disconnected from the source) make contact with trees and such high impedance material [7]. In most cases incidence of HIF results in electric arcing and possibly fire incidences. Also, studies have shown that HIF signals have numerous frequency harmonics which include both low and high harmonic components [8].

Over the years, several models have been developed to characterise [9]. Specifically, the work in [10] presented a single resistor-based HIF model, [11] presented arc-based HIF model, while [12] presented anti-parallel two diodes-based HIF model. Modeling of HIF provides means of detection, classification and location of HIF in power system networks. In order to promptly and properly manage the incidence of HIF in power networks, measurements of relevant network parameters are made,

suitable HIF detection technique is then selected based on the specific parameters measured, then, HIF classification technique is employed to determine the category of the HIF that has occurred based on the extracted features. Finally, fault location technique is employed to estimate the location of the HIF incidence on the power system network. Among the numerous HIF feature extraction techniques, the wavelet transform-based approach has been the most effective and the most widely used [13,14]. In addition, intelligent algorithms like artificial Neural Network (ANN) and fuzzy logic have been adjudged among the most effective HIF classifiers. As such, in this work, Discrete Wavelet Transform (DWT) method is employed for HIF feature extraction [15] while the Adaptive Neuro-Fuzzy Inference System (ANFIS) which is a combination of ANN and fuzzy technique is used in the HIF classification. Specifically, the discrete wavelet transform (DWT) is used to analyse the current signals obtained from an 11 kV distribution lines in Eket town covering Eket-Oron Road, Ekpene Ukpa Street, Ikot Nkwo Street, RCC Road - Idua Road, Court Road, Nkwo Udo Street and Ukwa Road. This network has a total of six 11 kV/ 0.415 kV power substations and one 33/11kV power injection substation as shown in the MATLAB/ SIMULINK model of Figure 1.

The research was conducted on 11kV/ 0.415 kV power distribution network (PDN) in Eket town. The case study 11 kV / 0.415 kV PDN in Eket town covers Eket-Oron Road, Ekpene Ukpa Street, Ikot Nkwo Street, RCC Road - Idua Road, Court Road, Nkwo Udo Street and Ukwa Road. This network has a total of six 11 kV/ 0.415 kV power substations and one 33/11kV power injection substation as shown in the MATLAB/ SIMULINK model of Figure 1.

The case study PDN was modelled using MATLAB/SIMULINK program. HIF of different categories were introduced at various locations near Nkwo Udo Street and other locations along the distribution network on the model. The three phase current signal data obtained from the MATLAB/Simulink simulated HIF were analysed using discrete wave transform (DWT) to obtain the data that are used for the training of the ANFIS for the detection as well as for the classification of HIF. The input dataset for the ANFIS HIF detector and classifier modelled in the MATLAB/SIMULINK program are the standard deviation obtained by DWT analysis of HIF current signal for each of the phases in the three phase system, as presented in Table 1. The flow diagram for this research methodology is presented in Figure 2 which indicates the various tasks and procedures carried out to achieve the main and specific objectives of this research.

2. METHODOLOGY

2.1 DESCRIPTION OF THE CASE STUDY POWER DISTRIBUTION NETWORK AND THE RESEARCH PROCEDURE

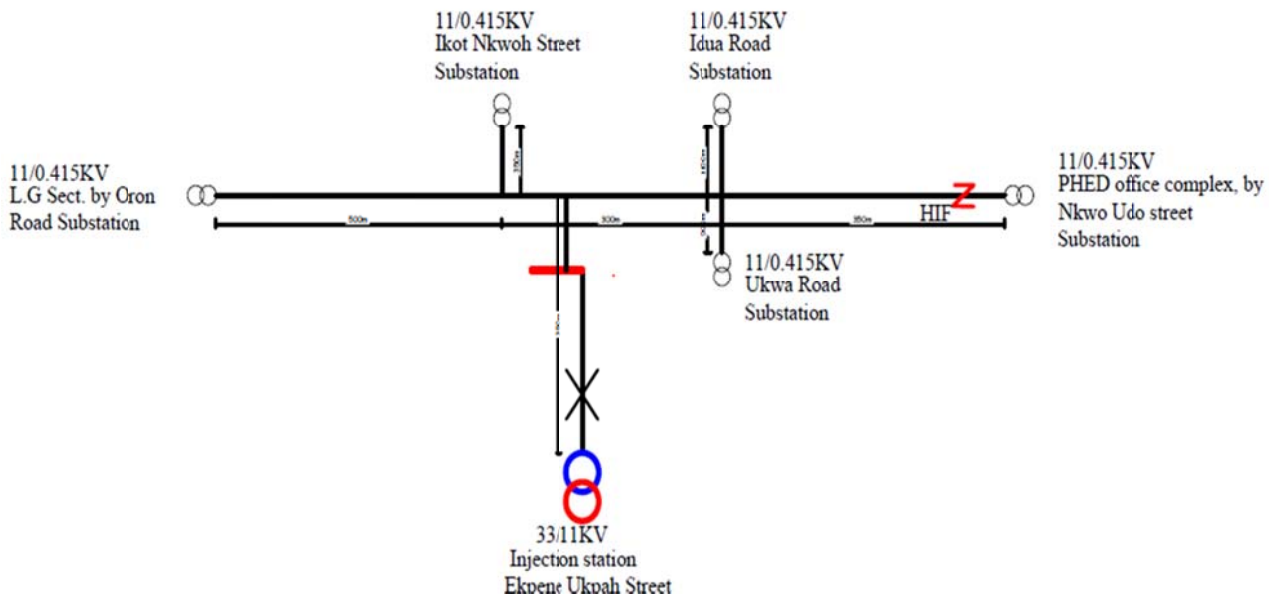


Figure 1: Single line diagram of the case study 11kV/0.415 kV distribution at Eket.

Table 1: Line parameters for 11 kV / 0.415 kV distribution network, Eket town.

Line Parameter	Per Unit Length Resistance (Ω /km)	Per Unit Length Inductance (mH/km)	Per Unit Length Capacitance (nF/km)
Positive Sequence	0.5160	0.7581	9.52
Zero Sequence	0.2710	3.1021	6.75

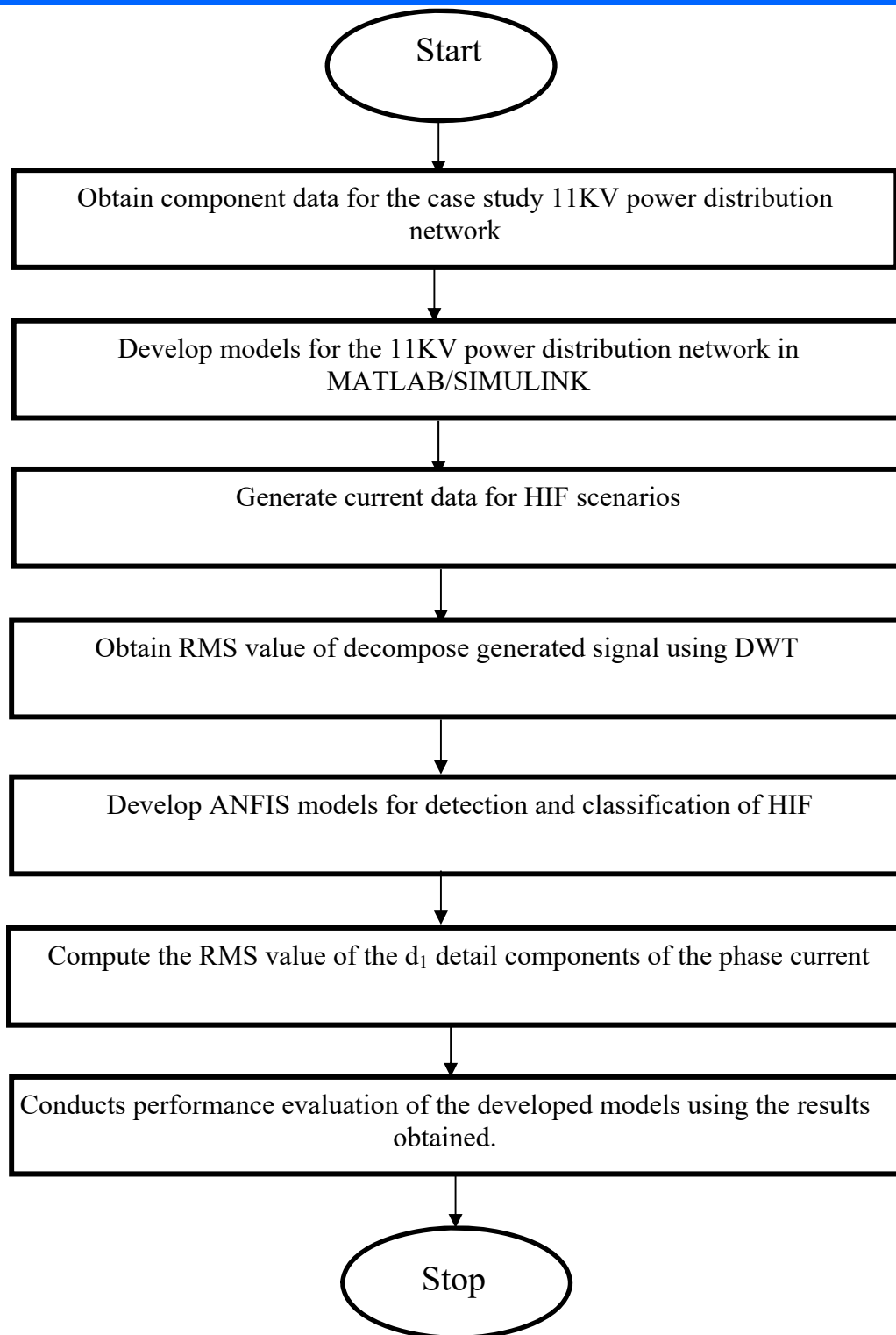


Figure 2: Flowchart of research methodology.

2.2 FAULT FEATURES EXTRACTION WITH DISCRETE WAVELET TRANSFORM (DWT)

High impedance fault signals are always of very low strength in nature. Therefore, Fourier transform and its variants are actually inadequate to analyse such low strength signals. Wavelet transforms are used as one of the best and appropriate tools for such signal analysis. Wavelet transforms divides up the signal into different frequency components, which are then evaluated separately with a resolution that matches the corresponding scale of each component.

In this work, Daubechies wavelet (dB5) is employed because of its known high performance in fault analysis [16]. The wavelet description dataset and associated parameters are as presented in Table 2. The three current signal waveforms associated with the different HIF fault conditions were measured and employed in the analysis. From pre-analysis of the HIF current signals, d_1 details component was observed to contain a good harmonic content that could be used to identify HIF. Therefore, only d_1 detail was used in this work.

Table 2: Description of wavelet and associated parameters.

Parameters	Properties
Mother wavelet	Doubechies, dB5
Sampling frequency	50 kHz
Information analyzed	Details: d ₁
Number of samples per cycle	5000
Occurrence of fault	Third cycle
Data window length analyzed	One cycle (0.1ms)

The RMS values were computed using Equation 1.

$$D_{rms} = \sqrt{\frac{\sum(x[n]-\bar{x}[n])^2}{N}} \quad (1)$$

where, D_{rms} is the RMS value of the detail components, $x[n]$ is the value of the detail components at discrete time n , $\bar{x}[n]$ is the mean value of the detail components and N is the samples used for the analysis.

2.3 MODELLING OF ANFIS-BASED FAULT DETECTION AND CLASSIFICATION

The ANFIS-based HIF detection model developed is presented in Figure 3. It has three inputs (PhA_rms, PhB_rms and PhC_rms) and an output (FD). The values of

the RMS of the d_1 detail components of phases A, B and C of the PDN line under consideration are the inputs to the ANFIS model, while the outputs are binary values that indicates the state of the PDN line (i.e. 0 – no fault, 0 – shunt faults and 1 – High impedance fault). When a fault incidence is detected, a trip signal is sent which then opens the line PI measurement block. The 5000 sets of the simulation data are divided into three groups which consist of 70 % (of dataset used for training) and 15 % (of dataset used for validation of the model) and 15 % (of dataset used for testing of the model). The description of the parameters used for the training and modelling of the ANFIS-based fault detection model are given in Table 3.

Table 3: Parameters for fault detection and classification ANFIS modelling.

Parameters	Values
Number of inputs	3
Membership functions per input	4
Membership functions Type	Gaussian combination
ANFIS generation method	Grid partition
Number of output	1
Number of fuzzy rules	64
Training data	497
Validation/ checking data	107
Testing data	107

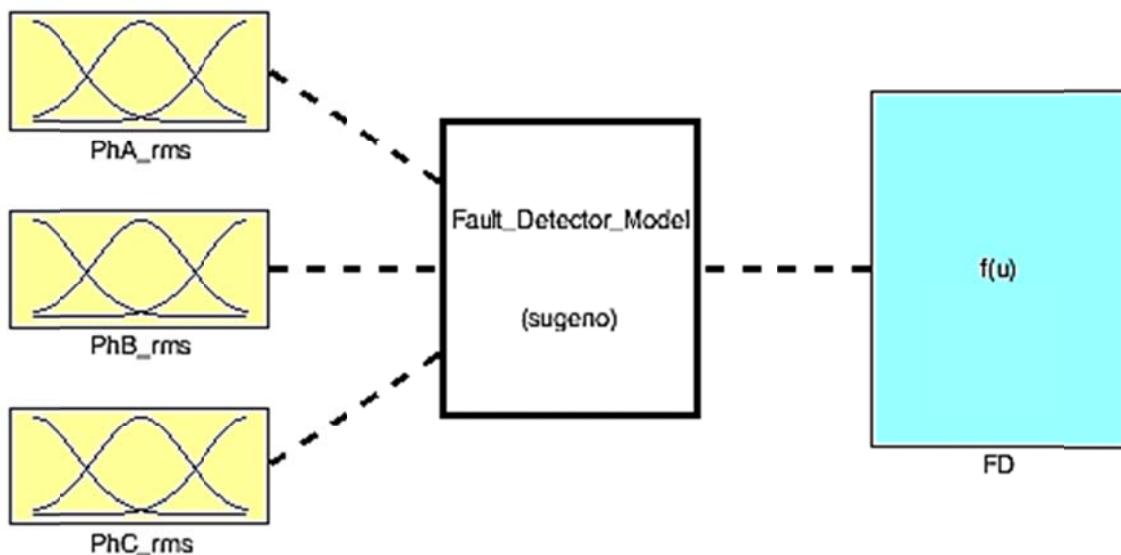


Figure 3: Block diagram of ANFIS-based fault detection model.

3. RESULTS AND DISCUSSION

MATLAB / SIMULINK environment was used for the development and simulations of the case study distribution network and DWT-ANFIS models. Power transformer, transmission lines, circuit breakers, current measuring

instruments, loads and fault blocks were used in Matlab/Simulink for modeling of the 11 kV / 0.415 kV distribution network at Eket town. Fault features extraction and development of ANFIS models were coded with MATLAB m-script environment.

3.1 RESULTS OF THE FAULT FEATURE EXTRACTION

The plot in Figure 4 shows the simulated current waveform for the single phase to ground HIF on line A. The fault feature was extracted using DWT. The simulated signal, the approximation (a5), and the details (d₁ - d₅) of each of the phases are presented in Figure 5 where a L-HIF (phase A) occurred. Similar results are shown in Figure 6 where a L-HIF (phase B) and in Figure 7 where a L-HIF (phase C). The DWT decomposition results for single phase to ground HIF on phase A is shown in Figure 8. The DWT decomposition results for single phase to ground HIF on phase B is shown in Figure 9 and the DWT decomposition results for single phase to ground HIF on phase c is shown in Figure 10.

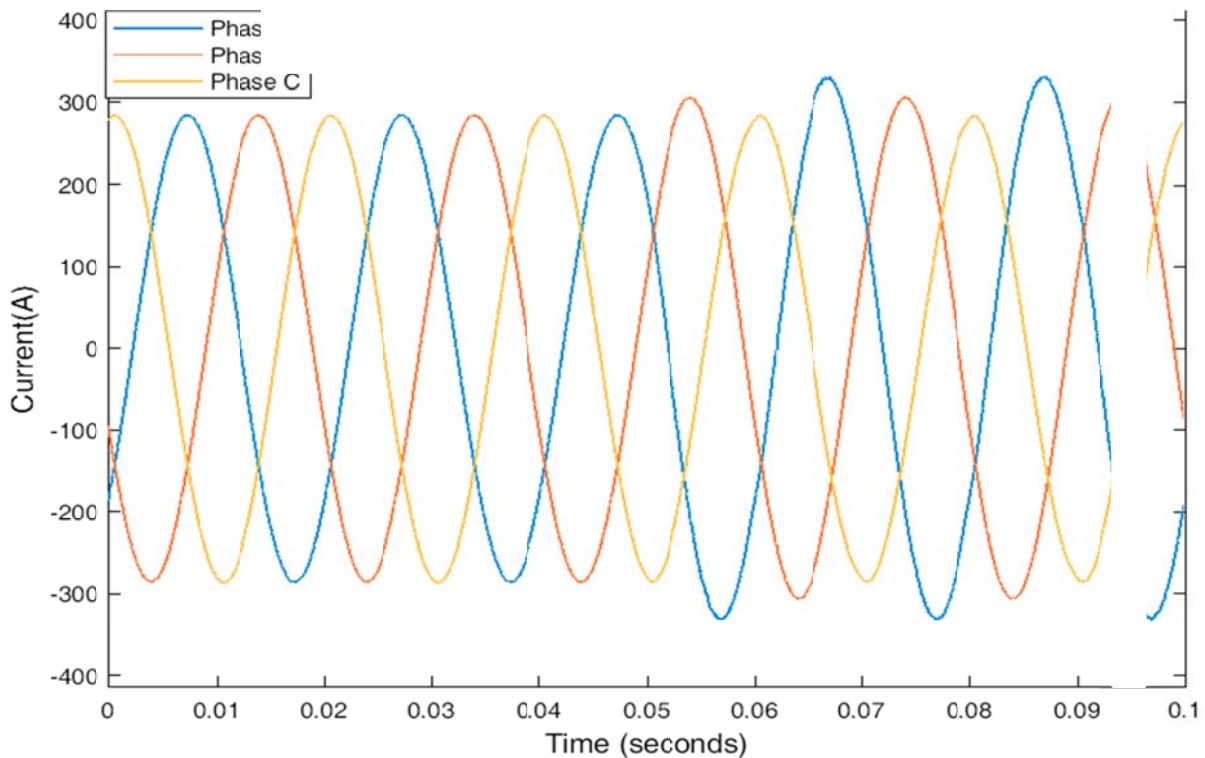


Figure 4: Current waveform of single phase to HIF on line A.

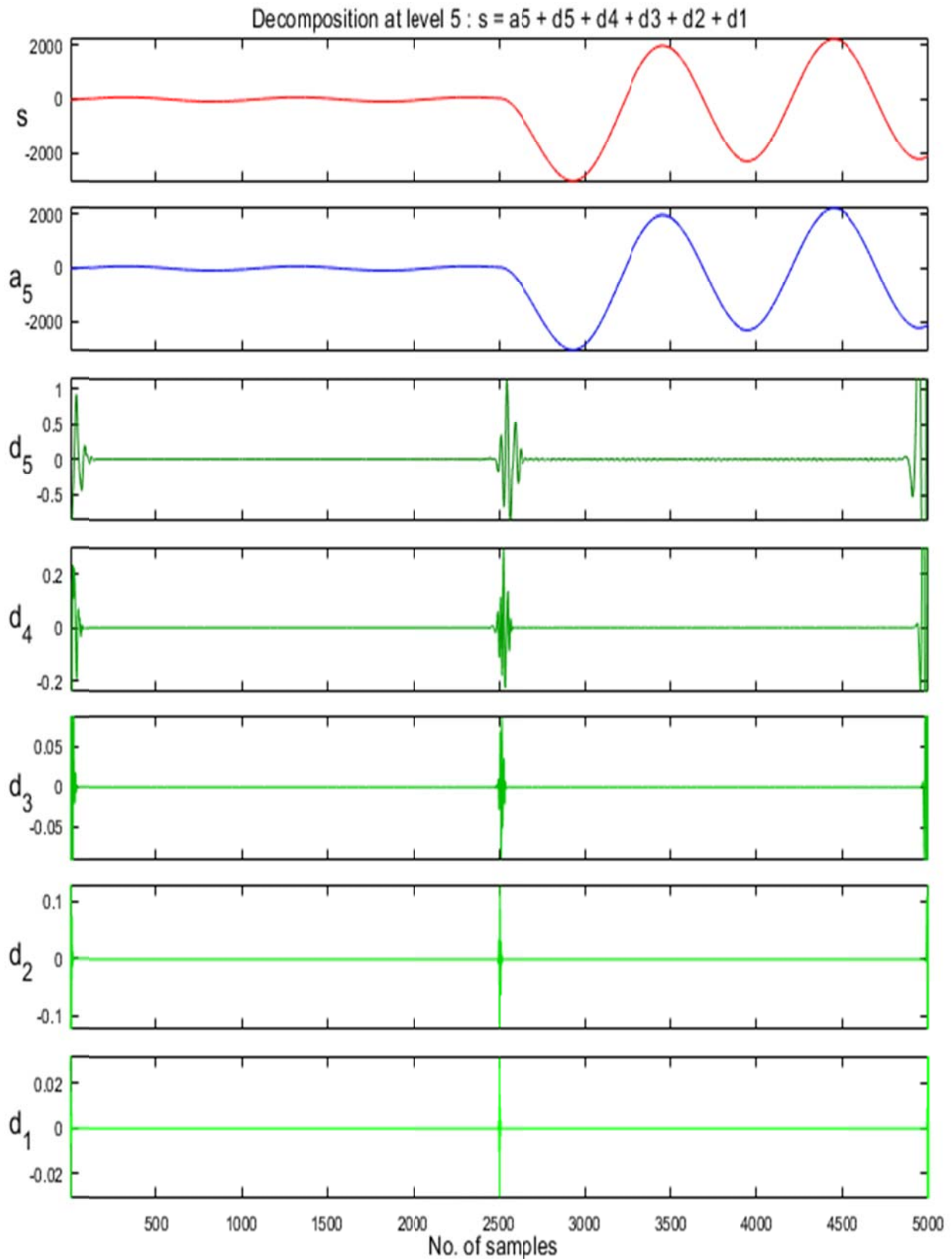


Figure 5: DWT decomposition of phase A.

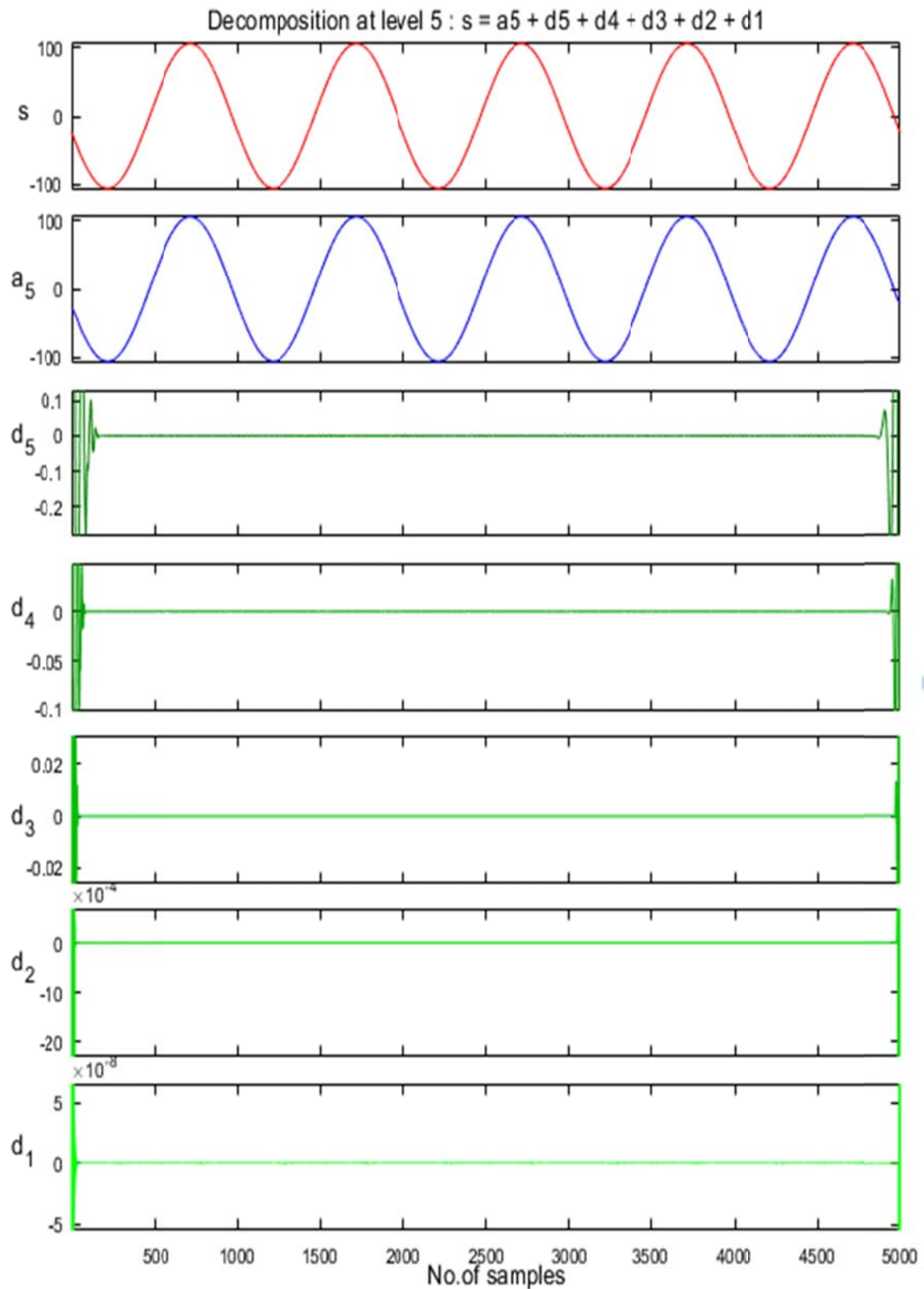


Figure 6: DWT decomposition of phase B.

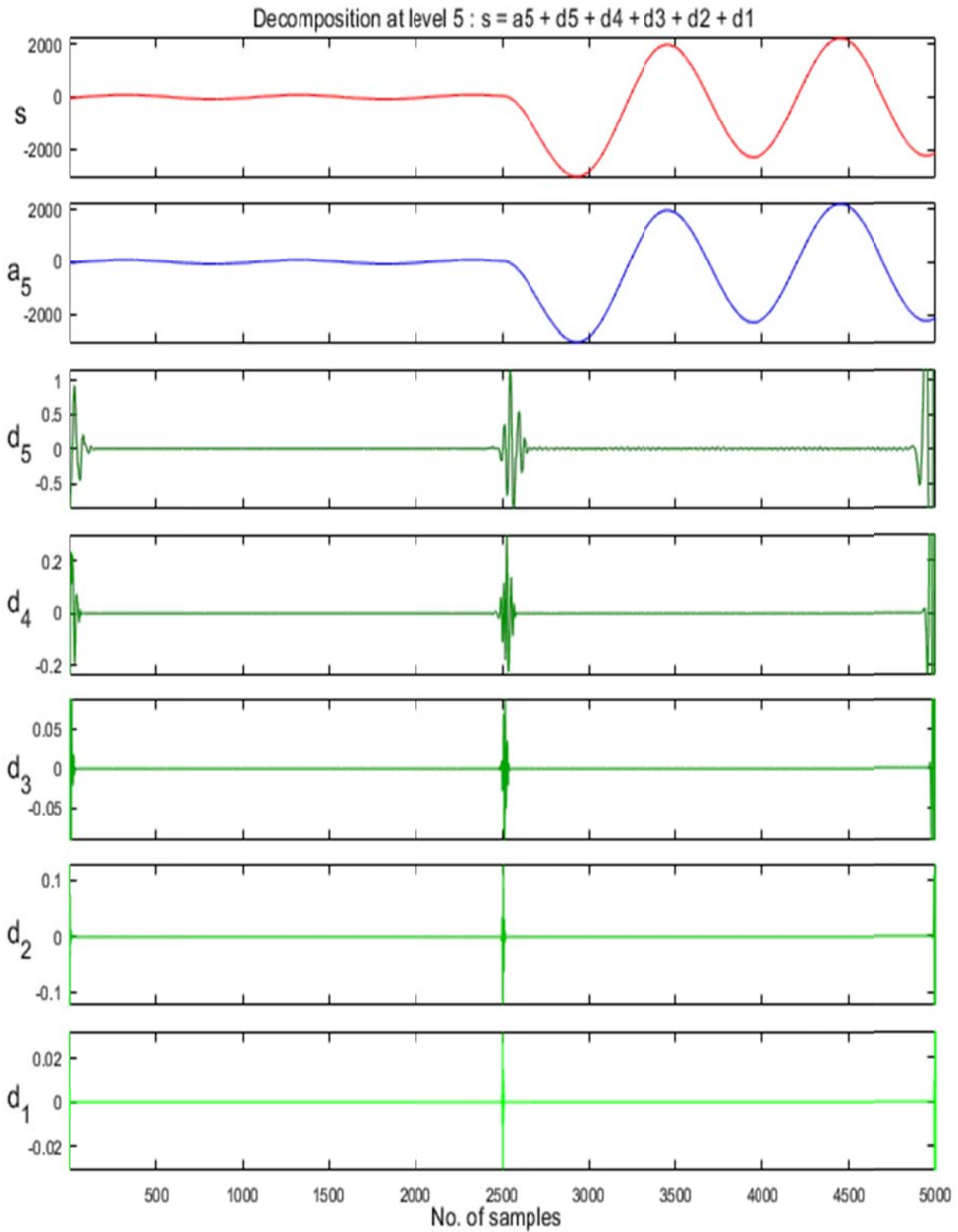


Figure 7: DWT decomposition of phase C.

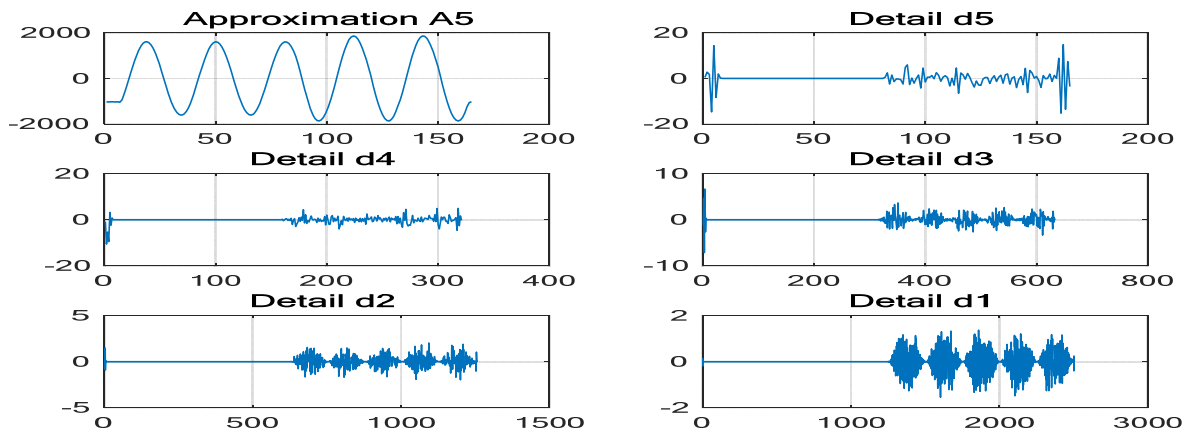


Figure 8: DWT decomposition results for single phase to ground HIF on phase A.

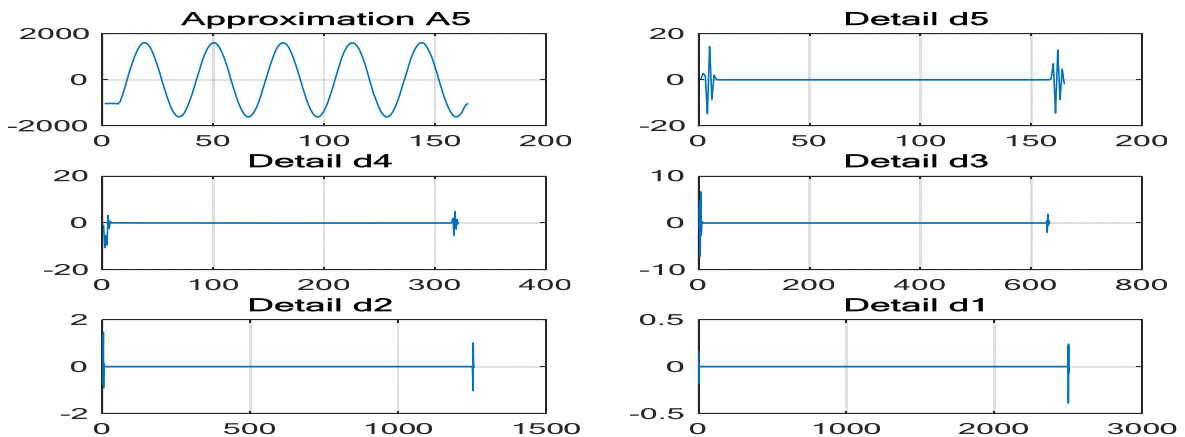


Figure 9: DWT decomposition results for single phase to ground HIF on phase B.

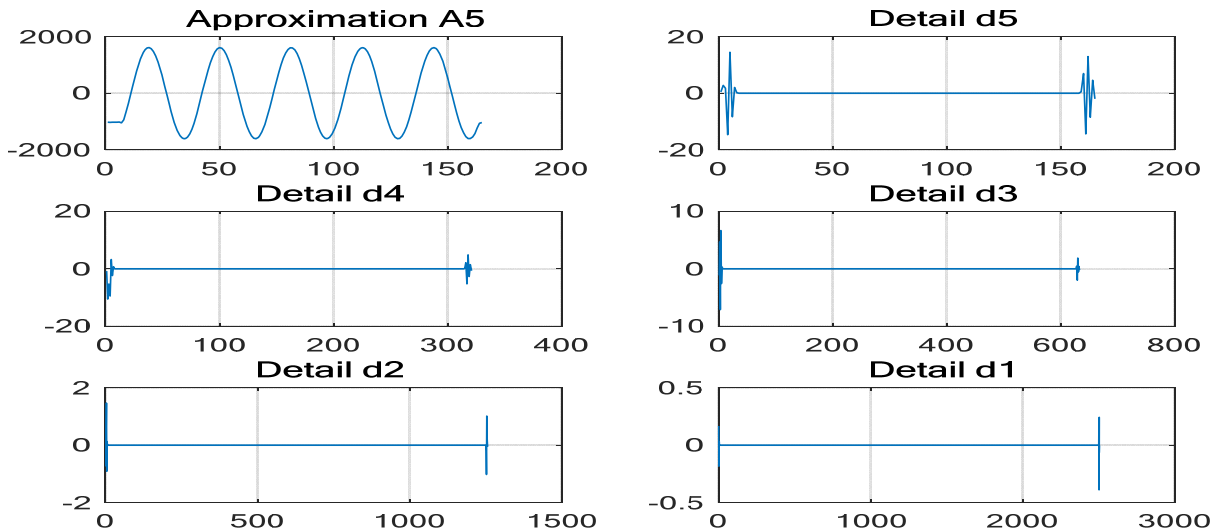


Figure 10: DWT decomposition results for single phase to ground HIF on phase C.

3.2 RESULTS ON FAULT DETECTION AND CLASSIFICATION USING DWT AND ANFI

The results presented in Table 4 are obtained from the ANFIS-based HIF detector. The phase to ground HIF and phase to phase HIF are detected as zero (0) due to the configuration of DWT in MATLAB/ SIMULINK environment. In the same vein, A-HIF, B-HIF and C-HIF are single phase to high impedance faults (HIF); AB-HIF, BC-HIF and AC-HIF are double phase to HIF.

Table 4: Fault detector output for different fault scenarios

The RMS values of each phase current (feature extracted by DWT) serves as the inputs while the output is either “0” (no fault) or “1” (HIF). The faults injection time of the faults simulator blocks for the different scenarios is also presented in Table 5. Also, Figure 8 presents the results of the current waveform of three phases fault after the circuit breaker tripped off.

Fault Type	RMS Value of d1 Coefficients			HIF Detection
	Phase A	Phase B	Phase C	
Normal	0	0	0	0
HIF A	0.1649	0.0255	0.0255	1
HIF B	0.0256	0.1663	0.0256	1
HIF C	0.0254	0.0254	0.1593	1
HIF AB	0.1748	0.1751	0.0265	1
HIF AC	0.1724	0.0267	0.1683	1
HIF BC	0.027	0.1746	0.167	1
HIF ABC	0.1815	0.1826	0.1749	1
Shunt Faults	0	0	0	0

Table 5: Fault detection output for different HIF scenarios.

Fault Type	Fault Time (sec)	RMS Values			Fault Detector (output)
		Phase A	Phase B	Phase C	
A-HIF	0.01	1.2987	0.0090	0.0075	1
B-HIF	0.02	0.0132	0.6875	0.1070	1
C-HIF	0.03	0.1029	0.0085	0.5696	1
AB-HIF	0.04	1.3729	1.3732	0.1067	1
BC-HIF	0.05	0.0024	0.2808	0.3800	1
AC-HIF	0.06	1.2698	0.0082	1.2701	1
AB-HIF	0.07	1.5527	1.1047	0.0069	1
BC-HIF	0.08	0.0037	0.5400	0.5061	1
AC-HIF	0.09	1.4035	0.085	0.0472	1
ABC-HIF	0.1	1.6450	1.0429	0.8511	1

3.3 DISCUSSION OF RESULTS

In this research, DWT-ANFIS is used to decompose the current signals into approximation and detail components. The RMS values of the details of each phase served as the feature from the current signals used for detection of HIF and also for classification of HIF. The waveform in Figure 4 shows that the HIF current of phase A has exceeded the set threshold value which is 5 p.u.. When the results of the faulty phase decomposition conducted using the DWT of (Figure 5) are compared with those obtained for other phases (Figures 6 and 7) the results show that the amplitude of the faulty phase is much higher for all the detail levels (d1 – d5). This result is also in agreement with the results presented in Table 4.

Also, as shown in Table 5, the developed HIF detector was able to discriminate between actual HIF cases from non HIF conditions as well as inrush current condition. Equally, the results show that the maximum tripping time from HIF occurrence is 0.01 milliseconds (Figure 8). This mean that the HIF is detected within one cycle of fault occurrence. This shows a 99.8% ability of the developed model to detect HIF in the case study distribution network.

Comparing the results of this research with the results obtained in a similar research on detection of HIF and for the location of HIF in low voltage DPN using ANN by [17], showed that ANFIS has a better HIF detection capacity. The authors in [17] carried out a study to detect and locate HIF in low voltage PDN located in Uyo using ANN. The results they obtained indicated that ANN gave 98.6% accuracy in detecting HIF whereas ANFIS would have produced 100% detection of HIF. Also, comparing the results obtained in this research with another related work on detection and classification of HIF on distribution

network using ANFIS and discrete wavelet transform carried by [18] indicates that ANFIS has the capabilities to perform a 100 % detection and classification of HIF on low voltage distribution network like the one used as a case study in this research. Finally, the RMSE values of the DWT-ANFIS classifier were 0.00007 and 0.00011 for the training of the model and also for the testing data respectively.

4. CONCLUSION

In this work of High Impedance Fault (HIF) detection framework and HIF classification scheme based on Discrete Wavelet Transform (DWT) and Adaptive Neuro Fuzzy Inference System (ANFIS) for a case study distribution network was developed. Root mean square (RMS) of the DWT decomposition of the current signals waveform were used to detect HIF occurrence and classify it using ANFIS. Simulation were done for a large number of sampling scenarios with HIF occurring in different phases of the case study distribution system and the performance of the proposed scheme was studied. Notably, the DWT and ANFIS-based framework was effective in discriminate between HIF cases from normal conditions as well as faults condition that were not HIF within a maximum time of 0.01 milliseconds. The HIF detection and classification were exact and were achieved with a very low RMS value of current with very high accuracy.

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