High Impedance Fault Classification And Location On 11KV/ 0.415 KV Power Distribution Network Using Dwt And Anfis

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Abstract*— In this paper, high impedance fault (HIF) classification and location on 11kV/ 0.415 kV Power Distribution Network (PDN) using Discrete Wavelet Transform (DWT) and Adaptive Neuro Fuzzy Inference System (ANFIS) is presented. In this work, MATLAB/Simulink package is used model the case study power distribution network (PDN) and to generate the fault signals to which the fault detection, classification and location mechanism are employed. Specifically, the DWT is used for fault feature extraction and then the Adaptive Neuro Fuzzy Inference System (ANFIS) is used for the fault detection, classification and location estimation. The case study 11 kV / 0.45 kV distribution network has six three phase pi – section line blocks and the fault conditions were set within the three phase fault blocks. The fault blocks were positioned at different locations to achieve the expected results. In the study, 5000 different HIF scenarios were introduced at different locations at 50 kHz sampling rate and fault times of 0.1 and 0.05 seconds respectively. The extraction and analysis of the fault features were conducted using the fault current of the three phases. The results show that the DWT-ANFIS HIF type classification has RMSE of 0.00007 for the training dataset and RMSE of 0.00011 for the testing dataset. Also, the DWT-ANFIS fault surface resistance classification has RMSE of 7.7189 for the training dataset and RMSE of 8.9389 for the testing dataset. The results captured 10 different HIF categories and a total of 30 different HIF faults. The results of the DWT-ANFIS HIF location estimator show that the r2 value is approximately 1 in all the HIF scenarios considered. In addition, the DWT-ANFIS HIF location estimator has maximum RMSE of 0.01977 km and maximum absolute error of 0.040960 km.

Keywords*— High Impedance Fault, Power Distribution Network, fault Location, Discrete Wavelet Transform (DWT), Adaptive Neuro Fuzzy Inference System (ANFIS)

1. INTRODUCTION

Distribution networks (DNs) are essential means of conveying of electric energy from injection substations to the consumers' distribution power substations through a very short distance [1,2]. These distribution networks are sometimes subjected to adverse atmospheric conditions and terrains that may lead to the incidence of high impedance fault (HIF) [3,4]. Notably, HIF in DNs mostly occur when one or more live conductors come in contact with high impedance surfaces (HIS) [5,6,7]. Under HIF conditions, distribution power networks (PDNs) are exposed to undue stress and conditions that pose great danger to the PDN and which may also damage the PDN as well as adversely affect the stability and quality of the power system [8,9,10]. It is therefore expedient to prevent the occurrence of HIF and promptly respond to the incidences of HIF by clearing overgrown vegetation towards distribution lines and by providing support under distribution lines to avoid coming in contact with HIS like grass and coal tar [11,12,13,14].

Furthermore, fault detection and classification on distribution lines are not enough, accurate determination of the fault location is essential for prompt response; possibly immediate isolation of the faulty section of the DN and also prompt repairs on the faulty section of the DN [15,16,17]. Accordingly, in this work, an efficient framework for the HIF detection, classification and most importantly HIF location estimation on PDNs is developed. This framework combines the feature extraction capability of Discrete Wavelet Transform (DWT) and the intelligent classification capability of Adaptive Neuro Fuzzy Inference System (ANFIS) [18,19]. Sample case study 11kV/ 0.415 kV Power Distribution Network (PDN) located in Eket, Akwa Ibom State Nigeria is used in the study. The PDN along with the DWT-ANFIS framework are modelled in

MATLAB /Simulink software. Root mean square error, absolute percentage error and r-square value are used as performance metrics for assessment of the DWT-ANFIS framework for HIF classification and location estimation.

2. METHODOLOGY

Power distribution network fault location estimation is part of general power transmission line fault analysis which includes fault detection, fault classification and fault location estimation, as shown in Figure 1. In this work, MATLAB/Simulink package is used and it requires modelling the power distribution network (PDN) in the MATLAB/Simulink environment and using the software to generate the fault signals to which the fault detection, classification and location mechanism are employed. In any case, the focus of this work is on the fault location estimation using the combined algorithms of Discrete Wavelet Transform (DWT) for fault feature extraction and then the Adaptive Neuro Fuzzy Inference System (ANFIS) for the fault detection, classification and location estimation.

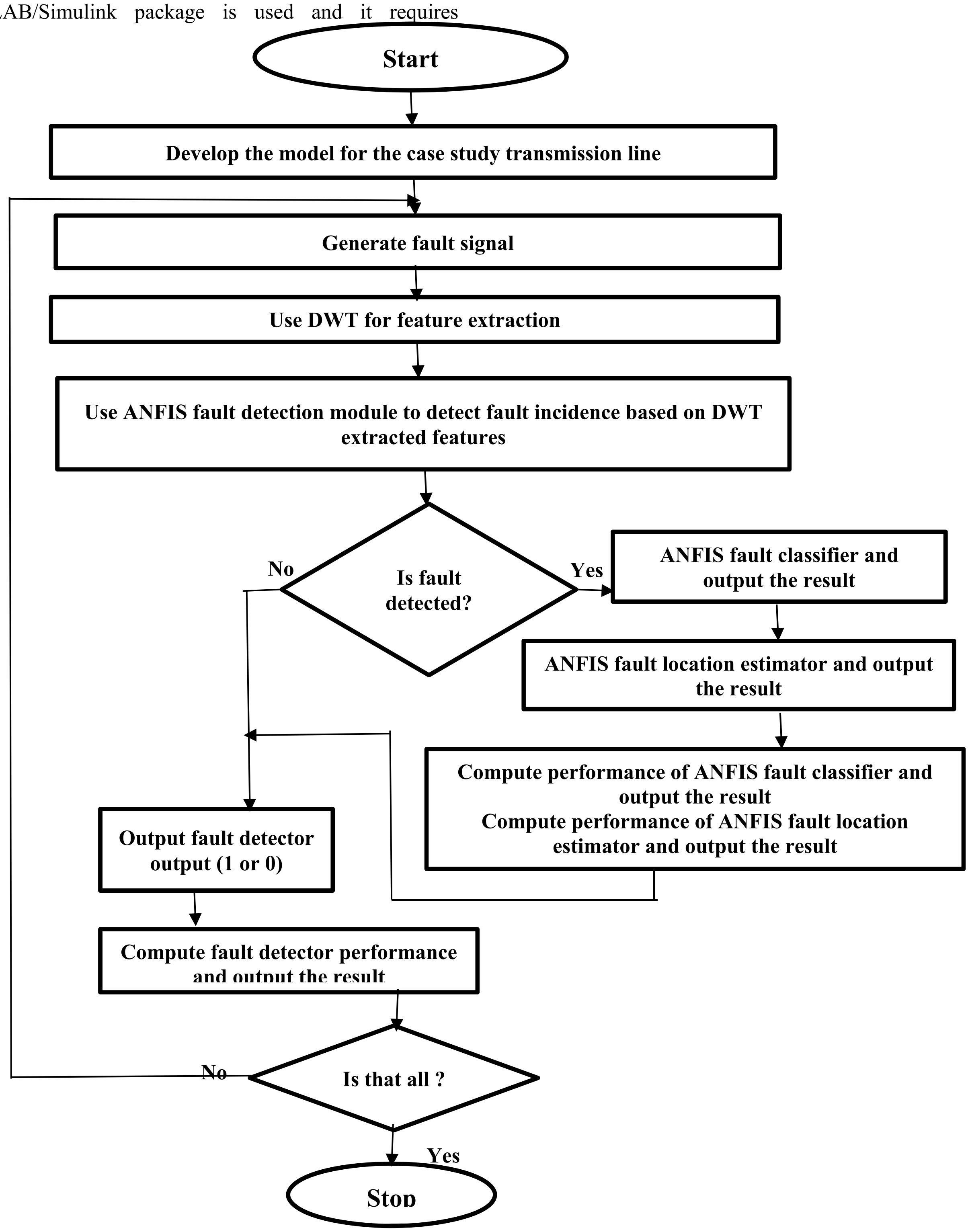

Figure 1 The comprehensive flow diagram for transmission line fault analysis

2.1 MODELING OF THE CASE STUDY 11 KV/0.415 KV DISTRIBUTION ON MATLAB/SIMULINK NETWORK

The MATLAB / SIMULINK developed for the simulation of different fault conditions at different locations in the case study 11 kV / 0.415 kV distribution network at Eket town is shown in Figure 2. The case study 11 kV / 0.45 kV distribution network was actually achieved with six three phase pi – section line blocks and the fault conditions were set within the three phase fault blocks. The fault blocks were positioned at different locations to achieve the expected results. The locations of the six P-I blocks are indicated on the MATLAB/SIMULINK model of Figure 2. Load blocks were also introduced to serve as terminal loads which are connected to the line through a step-down transformer block of 11/0.415 kV.

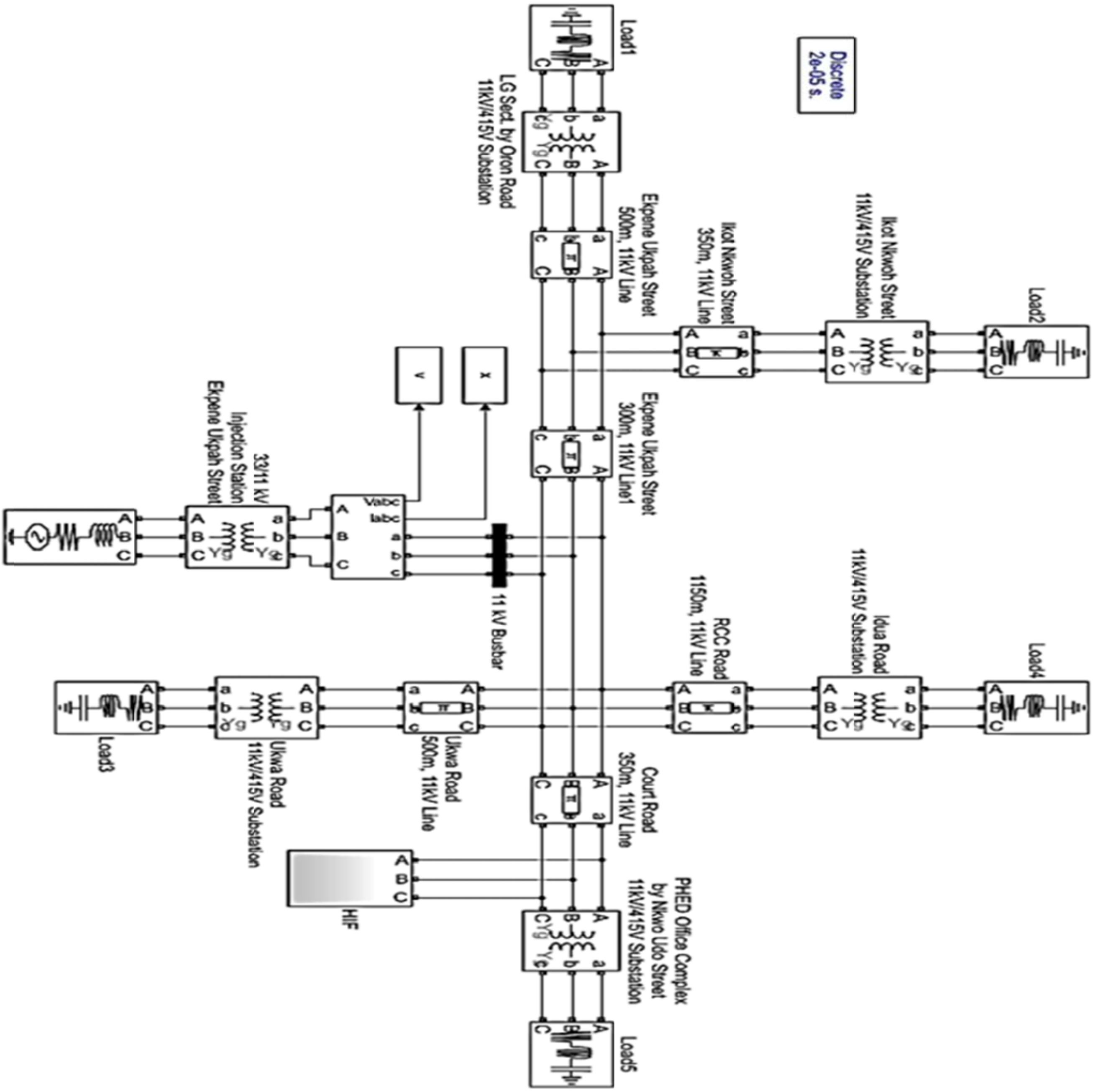

Figure 2: MATLAB/ SIMULINK model of the case study distribution network.

2.2 GENERATION OF FAULT DATA

In the study, 5000 different HIF scenarios were introduced at different locations at 50 kHz sampling rate and fault times of 0.1 and 0.05 seconds respectively. The extraction and analysis of the fault features were conducted using the fault current of the three phases.

The main concern of this research is to first detect the incidence of HIF on the case study 11kV/ 0.415 kV PDN and thereafter determine the fault type and then estimate the location of the fault. High impedance faults (HIF) are always associated with low flow of fault current whenever they occur making them very difficult to detect and classify. One good feature of HIF that can aid determination and discrimination from other shunt faults is the presence of high content of harmonic. In order to extract this harmonic feature, DWT is used in this work. The set of parameter values used in generating HIF currents values for the 11 kV/0.45 PDN at Eket town are as tabulated in Table 1.

Table 1: The set of parameter values used in generating HIF currents values for the 11 kV/0.45 PDN at Eket town

Parameter	Set values
Fault Type Surfaces	HIF_A, HIF_B, HIF_C, HIF_AB, HIF_AC, HIF_ BC, HIF_ABC,ABC_G, A_G, B_G, C_G, AB_G, AC_G, BC_G, BC, ABC, No fault.
Fault Resistance (Ω)	20 -500 Ω
Firing angle	$0^{o} – 180^{o}$
Fault Time (s)	0.05

2.3 MODELLING OF ANFIS-BASED HIF SURFACE TYPE

The ANFIS fault classification model presented in Figure 3 and has four inputs, the load on fault and the average RMS value of the d_1 component of phase A, B, C and zero sequence current of the case study distribution network under consideration. The **ANFIS-based HIF location estimator model is presented in Figure 4** and has four inputs, the fault type and the average RMS value of the d_1 component of phase A, B, C of the case study distribution network under consideration.

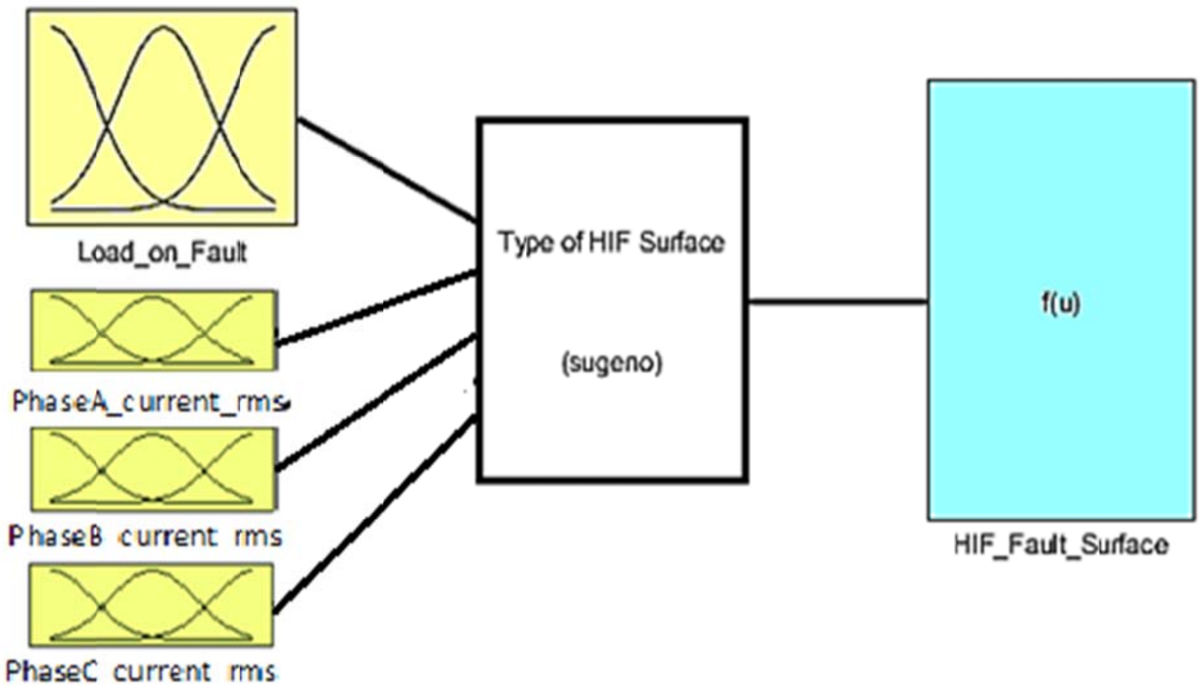

Figure 3: ANFIS-based HIF surface model.

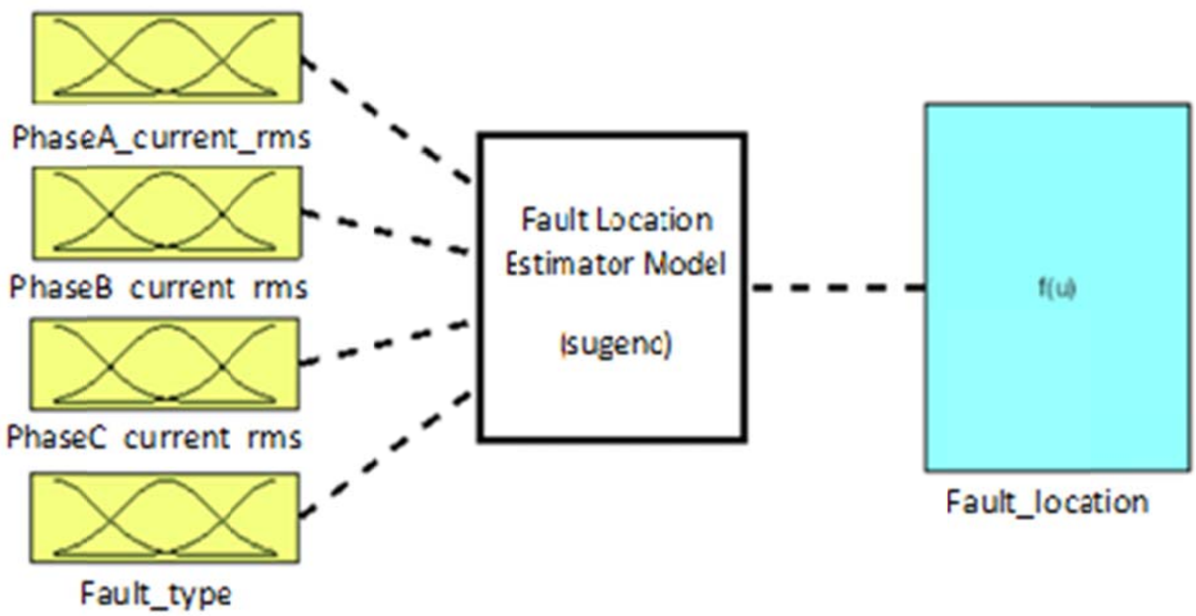

Figure 4: ANFIS-based HIF location estimator model.

The 5000 dataset employed in simulation were grouped into three different datasets which consists of 80 % (of the dataset meant for model training), 10 % (of the dataset meant for model validation) and 10 % (of the dataset meant for model testing). The description of the parameters employed in the ANFIS-based HIF classification model development are given in Table 2.

Table 2: Parameters for fault classification ANFIS model.

Parameters	Values
Number of inputs	2
Membership functions per input	5
Membership functions Type	Gaussian combination
FIS generation method	Grid partition
Number of output	1
Number of rules	64
Training data	497
Validation data	107
Testing data	107

2.4 PERFORMANCE INDICES

The following indices were used to evaluate the performance of the model:

i. ROOT MEAN SQUARE ERROR (RMSE)

The root Mean Square Error (RMSE) is computed using Equation 1.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i-1}^{n}(y_i - \bar{y}_i)^2} \quad (1)$$

Where y_i denotes the value observed (actual value), $\bar{y}_i$ denotes the value predicted and n denotes the number of observations.

ii. ABSOLUTE ERROR

This absolute error is computed using Equation (3).

$$|\mathrm{error}| = |x_p - x_o| \quad (2)$$

where x_o denotes the value observed (actual value) and x_p denotes the value predicted.

iii. COEFFICIENT OF DETERMINATION (R^2)

Coefficient of Determination (R^2) is computed using Equation 3.

$$R^2 = \frac{n(\sum xy)-(\sum x)(\sum y)}{\sqrt{[n\sum x^2-(\sum x)^2][n\sum y^2-(\sum y)^2]}} \quad (3)$$

where,x denotes the value observed (actual value), y denotes the value predicted and n denotes the number of observations.

3 RESULT AND DISCUSSION

Matrix Laboratory (MATLAB) software is used in the simulations conducted in this research. It was utilized for the modelling of the electric PDN and in the modelling of the DWT-ANFIS techniques used in this work.

3.1 RESULTS ON FAULT CLASSIFICATION

The ANFIS HIF classification model gives results as an integer and the integer value is as shown by Table 3.

Table 3.: Fault detection ANFIS model result

Fault Type	No Fault	Shunt Fault	A-HIF	B-HIF	C-HIF	AB-HIF	BC-HIF	AC-HIF	ABC-HIF
Values	0	0	1	1	1	1	1	1	1

The result of ANFIS output for HIF type classification for training and testing data are presented in Figure 5 and Figure 6 respectively while Figure 7 and Figure 8 present the plots of ANFIS output for fault surface resistance classification for training and testing data. The results show that the ANFIS output for HIF type classification has RMSE of 0.00007 for the training dataset (Figure 5) and RMSE of 0.00011 for the testing dataset (Figure 6). Also, the results show that the ANFIS output for fault surface resistance classification has RMSE of 7.7189 for the training dataset (Figure 7) and RMSE of 8.9389 for the testing dataset (Figure 8).

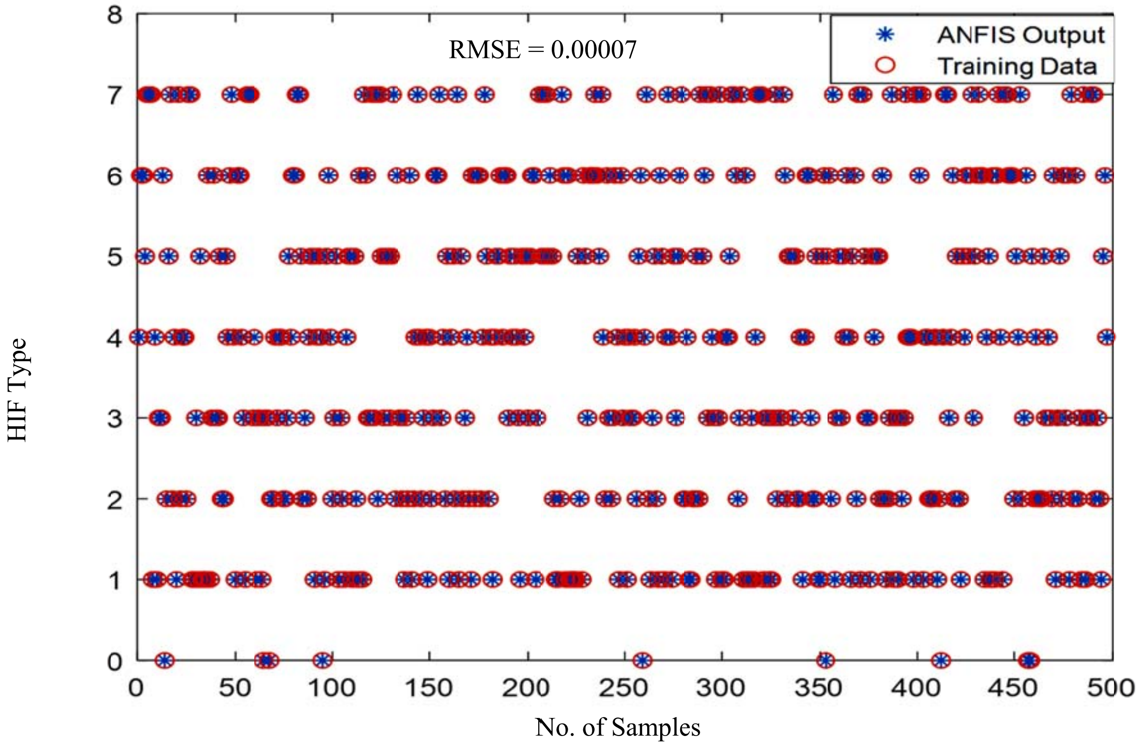

Figure 5: Plots of ANFIS output for HIF type classification for training data.

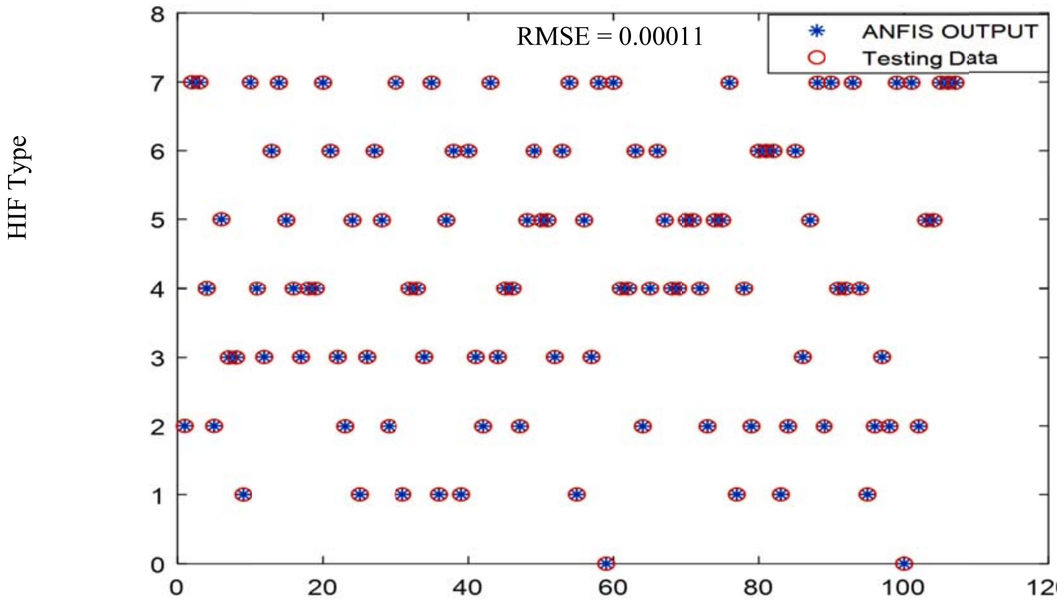

Figure 6: Plots of ANFIS output for HIF type classification for testing data.

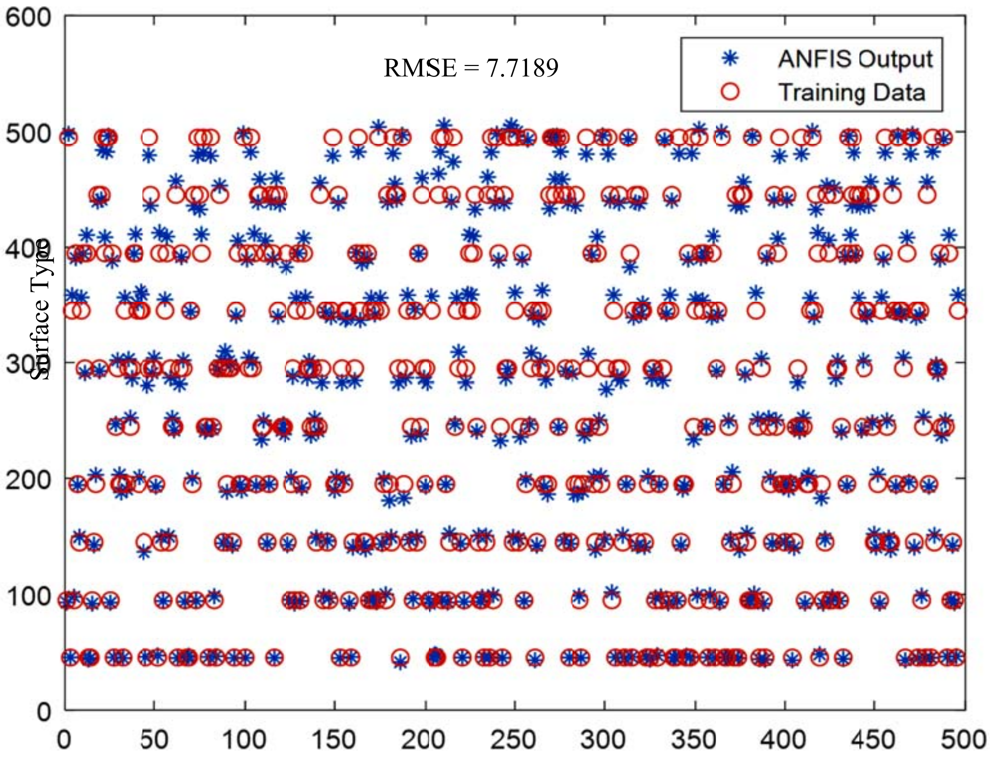

Figure 7: Plots of ANFIS output for fault surface resistance classification for training data.

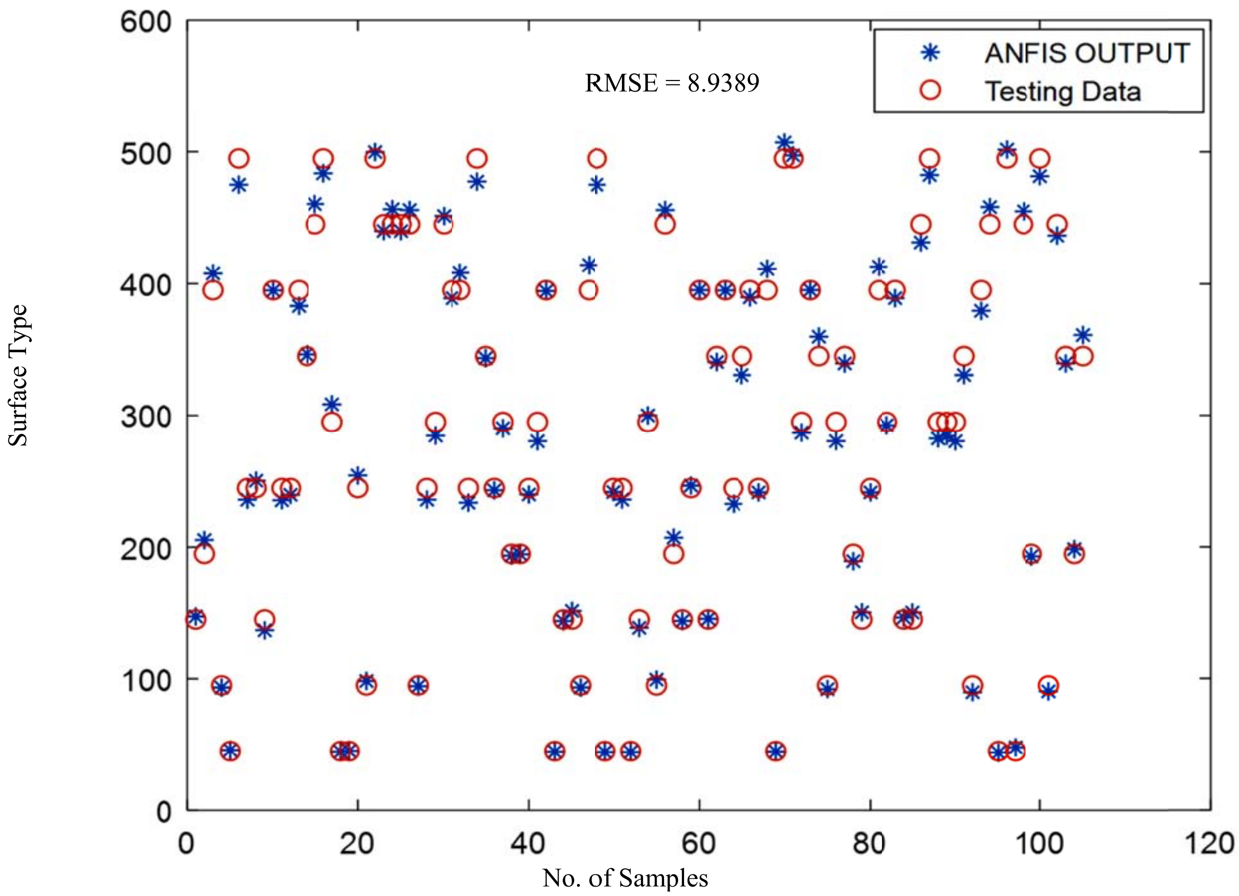

Figure 8: Plots of ANFIS output for fault surface resistance classification for testing data.

3.2 RESULTS ON FAULT LOCATION

The results of the DWT-ANFIS HIF location estimator are resented in Table 4 while the performance of the DWT-ANFIS HIF location estimator are resented in Table 5. The results captured 10 different HIF categories and a total of 30 different HIF faults. The results show that the r^2 value is approximately 1. The maximum RMSE is 0.01977 km and the maximum absolute error is 0.040960 km. In all, the DWT-ANFIS HIF location estimator is very good.

Table 4 The results of the DWT-ANFIS HIF location estimator

Fault Type @ Fault Resistance	Actual Distance (km)	Predicted Distance (km)	|error| km
AG@2.7Ω	0.1	0.10003	0.000030
AG@1.2Ω	59.3	59.30297	0.002970
AG@3Ω	91.7	91.68074	0.019260
BG@1.8Ω	23.7	23.6981	0.001900
BG@0.12Ω	94.8	94.80284	0.002840
BG@2.4Ω	99.8	99.78303	0.016970
CG@1.2Ω	35.6	35.61032	0.010320
CG@0.3Ω	71.1	71.09431	0.005690
CG@2.4Ω	89.3	89.26785	0.032150
AB@1.5Ω	11.9	11.89952	0.000480
AB@0.6Ω	47.4	47.4	0.000000
AB@2.7Ω	83	83.00664	0.006640
AC@0.9Ω	23.7	23.7045	0.004500
AC@0.12Ω	59.3	59.28873	0.011270
AC@2.4Ω	83	83.00083	0.000830
BC@1.2Ω	0.1	0.10005	0.000050
BC@0.9Ω	11.9	11.89607	0.003930
BC@0.12Ω	47.4	47.40806	0.008060
ABG@0.3Ω	23.7	23.67962	0.020380
ABG@2.1Ω	71.1	71.08934	0.010660
ABG@0.9Ω	99.9	99.85904	0.040960
ACG@2.7Ω	35.6	35.63062	0.030620
ACG@1.5Ω	83	82.96182	0.038180
ACG@1.2Ω	94.8	94.81138	0.011380
BCG@3Ω	11.9	11.89548	0.004520
BCG@1.8Ω	59.3	59.3	0.000000
BCG@0.9Ω	80	80.04	0.040000
ABC@3Ω	0.1	0.10002	0.000020
ABC@1.8Ω	47.4	47.41422	0.014220
ABC@0.6Ω	94.8	94.77156	0.028440

Table 5 The performance of the DWT-ANFIS HIF location estimator

S/N	Fault Type @ Fault Resistance	RMSE	|error| (%)	R^2
1	AG	0.011251	0.005 to 0.03	1
2	BG	0.009994	0.003 to 0.017	1
3	CG	0.01977	0.008 to 0.036	1
4	AB	0.003844	0 to 0.008	1
5	AC	0.007023	0.001 to 0.019	1
6	BC	0.005177	0.017 to 0.05	1
7	ABG	0.027121	0.015 to 0.086	1
8	ACG	0.02901	0.012 to 0.086	0.999 999
9	BCG	0.023241	0 to 0.05	1
10	ABC	0.018358	0.02 to 0.03	1

4. CONCLUSION

Classification and location estimation of High Impedance Fault (HIF) on a power distribution network (PDN) is presented. The HIF classification and location estimation is based on discrete wavelet transform and Adaptive Neuro Fuzzy Inference System (ANFIS). The case study PDN is located in Eket in Akwa Ibom State. The simulation was conducted using MATLAB /Simulink software. The results show that the DWT and ANFIS combined algorithm can effectively be used to detect, classify and estimate the location of HIF in PDN.

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