Comparative Analysis of Fuzzy Inference System (FIS) and Adaptive Neuro-Fuzzy Inference System (ANFIS) Methods in The Classification and Location of High Impedance Faults on Distribution System

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Abstract—Unlike low impedance faults, which involve relatively large magnitude of fault currents and are easily detected by conventional over-current protection devices, high impedance faults pose a serious challenge to protection engineers because they can remain on the system without the protective relays being able to detect them. This paper presents an improved method for detection and location of high impedance fault using ANFIS model. The study was conducted on the 33 kV Uyo-Ikot Ekpene power distribution line. The case study power distribution system was modeled using MATLAB software. HIFs were introduced at various locations along the distribution line. The data obtained from the MATLAB/Simulink simulated fault using discrete wavelet transform (DWT) were used to train the ANFIS for the location of HIF points along the distribution system as well as for prediction of the distance of the fault location to the nearest injection substation. The results show that ANFIS model gives 52.5 percentage reduction in error compared with FIS in the location of fault points on the case study power distribution system.

Index Terms—Classification, Distribution System, High Impedance Faults, 33 kV Line.

I. INTRODUCTION

High impedance faults are those faults with much resistance in the fault path [1], [2]. The magnitude of the fault resistance for a problem, defined as a high impedance fault is dependent upon interpretation and circumstances. High impedance faults are ground faults that produce fault currents below the standard ground overcurrent element pickup level [3], [4].

However, high impedance faults caused by downed conductors are potentially dangerous to humans and livestock and really are a concern for public safety. A high impedance fault ought to be rapidly isolated when sensed [5]. Conventional substation–based overcurrent defensive relays reliably detect high current, short-circuit faults. Exactly the same cannot be said about substation-based high impedance fault detection as a result of low or nearly zero fault current. Since early 1970s, the issue of high impedance faults has caught the interest of the people in addition to power protection engineers. As time passes, utilities worldwide have conducted many field tests to aid research and development of detection algorithms for these small current faults [6].

High impedance faults neither interrupt service to customers nor cause thermal harm to electrical system equipment due to low-fault currents [7], [8].

II. HIF ANFIS BASED DETECTION AND CLASSIFICATION METHODOLOGY

This part presents the procedure for classifying the HIFs in the medium voltage distribution system, as well as locating the fault points from the nearest injection substation.

Firstly, three phase current signal obtained using MATLAB simulation of the medium voltage distribution system are analyzed using DWT to get the data for training. The input to the ANFIS classifier and locator model are standard deviation values of each phase of three phase system obtained by DWT analysis of fault current signal obtained by MATLAB simulation of the distribution system, the output of the ANFIS is the type of fault that occurs in the system.

A. Fuzzy Inference System

Fuzzy inference system (FIS) is a system that uses fuzzy set theory to map inputs to outputs. It is a form of many-valued logic with a set of common sense rules. In addition, it is flexible and tolerant to imprecise data and natural language. It is an excellent platform for dealing with classification problems with noisy and incomplete information. FIS provides a non-linear input-output mapping method that converts a vector, which consists of features, into a scalar. This method is used to classify different types of faults that occur in the system and to locate the fault points in the system. The stages followed in training the FIS is shown in Fig. 1.

Stage 1: Problem definition and classification of the SD values (i.e. data)
Stage 2: Definition of input and output fuzzy sets with variable name
Stage 3: Define the type of membership function for each rules
Stage 4: Frame the rules
Stage 5: Build and test the system
Stage 6: Tune and validate the trained system

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Fig. 1: FIS Structure

The fuzzy system has three input i.e. $S_a$, $S_b$ and $S_c$ and one output. Four triangular membership functions have been chosen for every phase, They include, normal, fault, ground and high. The output membership function has 7 triangular membership functions named as normal HIF, L-G, L-L, L-L-G, L-L-L-L, and L-L-L-G fault.

The fuzzy rules are framed using $S_a$, $S_b$ and $S_c$ as phase A, phase B and phase C respectively as follows:

**i.** If $S_a$ is normal, and $S_b$ is normal and $S_c$ is normal, then trip output is normal.

**ii.** If $S_a$ is fault, and $S_b$ is normal and $S_c$ is normal, then trip output is A-B-C fault.

**iii.** If $S_c$ is normal, and $S_b$ is ground and $S_c$ is ground, then trip output is A-B-G fault.

**iv.** If $S_a$ is normal, and $S_b$ is ground and $S_c$ is ground, then trip output is B-C-G fault.

**v.** If $S_a$ is normal, and $S_b$ is ground, and $S_c$ is ground, then trip output is A-C-G fault.

**vi.** If $S_b$ is normal, and $S_c$ is normal and $S_a$ is ground, then trip output is A-G fault.

**vii.** If $S_a$ is normal, and $S_c$ is normal, and $S_b$ is ground then trip output is B-G fault.

**viii.** If $S_a$ is normal, and $S_b$ is normal, and $S_c$ is ground then trip output is C-G fault.

**ix.** If $S_a$ is normal, and $S_b$ is fault, and $S_c$ is fault, then trip output is A-B fault.

**x.** If $S_a$ is normal, and $S_b$ is fault, and $S_c$ is fault, then trip output is B-C fault.

**xi.** If $S_b$ is normal, and $S_a$ is ground, and $S_c$ is fault, then trip output is A-C fault.

**xii.** If $S_b$ is normal, and $S_a$ is ground, and $S_c$ is ground, then trip output is A-C fault.

**xiii.** If $S_a$ is normal, and $S_c$ is normal, and $S_b$ is HIF, then output is HIF at phase A.

**xiv.** If $S_a$ is normal, and $S_b$ is normal, and $S_c$ is normal, and $S_b$ is HIF at phase B.

**xv.** If $S_a$ is normal, and $S_c$ is HIF, and $S_b$ is HIF, then trip output is HIF at phase A.

**xvi.** If $S_a$ is normal, and $S_b$ is HIF, and $S_c$ is HIF, then trip output is HIF at phase A.

**xvii.** If $S_b$ is normal, and $S_a$ is HIF, and $S_c$ is HIF, then trip output is HIF at phase A.

**xviii.** If $S_b$ is HIF, and $S_a$ is HIF, and $S_c$ is HIF, then trip output is HIF A-B-C.

### B. Location of HIF

The HIF was located with ANFIS model after being simulated for different distances from Afaha Ube transmission station along Ikot Ekpene distribution line. Some of the simulation with SIMULINK for the predictions of fault points are presented in Fig. 2 and Fig. 3.

![Fig. 2: HIF location prediction when fault occurred at 1 km from Afaha Ube.](image-url)
C. ANFIS Locator

125 rules are framed for the location of fault point fuzzy membership function as shown in Fig. 4. This section presents the intelligent approach of locating the point of HIFs in the medium voltage distribution system.

The ANFIS structure of Fig. 5 comprises of five layers in the inference system. Each layer involves several nodes, which are described by the node function.

The ANFIS Fault point locator consists of three neurons in the input layer and three triangular membership functions for each input. It has a constant single membership function for the output. The output of the model shows the location of the point of fault.

The case study distribution system was simulated using MATLAB/Simulink with different types of HIF conditions where two different resistance values were obtained to represent the two different HIF surfaces available along the medium voltage distribution system, that is, vegetation and the ground. The training data was extracted from the simulation of the distribution system using DWT.

III. COMPARATIVE ANALYSIS RESULTS

Here, the comparative analysis of the proposed ANFIS system with the Fuzzy inference system approach is considered. The performances of these trained intelligent methods were measured by the success and discrimination rate of each method to classify and locate HIFs from other disturbances in the system.

The success rate and discrimination rate are defined by (1) and (2) respectively.

\[
\text{Success rate} = \frac{\text{No. of HIFs detected}}{\text{Total No. of HIF events}} \times 100 \quad (1)
\]

\[
\text{Discrimination rate} = 1 - \frac{\text{No. of events wrongly diagnosed}}{\text{Total No. of events}} \times 100 \quad (2)
\]

The results show that the success rate and discrimination
rate of FLS are 69 % and 85 % respectively whereas the ANFIS method of classification has the success rate and discrimination rate of 100 %.

For location of HIF points in the system,

\[ \text{Success rate}_1 = \frac{\text{No. of located HIFs}}{\text{Total No. of HIFs}} \times 100 \]  
(3)

\[ \text{Discrimination rate}_1 = 1 - \frac{\text{No. of events wrongly located}}{\text{Total No. of events}} \times 100 \]  
(4)

Percentage Reduction in error = \frac{\text{Error using FIS - Error using ANFIS}}{\text{Error using FIS}} \times 100 \]  
(5)

TABLE I: FAULT LOCATION ON PHASE A

| S/N | Fault Location @ Fault Resistance | Fault Location (ANFIS) | Error (ANFIS) | Fault Location (FIS) | Error (FIS) |
|-----|----------------------------------|------------------------|---------------|---------------------|-------------|
| 1   | 3.3km @ 250ohms                  | 3.30                   | 0.00          | 3.25                | 0.05        |
| 2   | 3.3km @ 300ohms                  | 3.19                   | 0.11          | 3.45                | 0.15        |
| 3   | 8.9km @ 250ohms                  | 8.80                   | 0.10          | 8.74                | 0.16        |
| 4   | 8.9km @ 300ohms                  | 8.91                   | 0.01          | 8.86                | 0.04        |
| 5   | 14.7km @ 250ohms                 | 14.70                  | 0.00          | 14.65               | 0.05        |
| 6   | 14.7km @ 300ohms                 | 14.72                  | 0.02          | 14.77               | 0.07        |
| 7   | 17.1km @ 250ohms                 | 17.14                  | 0.04          | 17.19               | 0.09        |
| 8   | 17.1km @ 300ohms                 | 17.06                  | 0.04          | 17.22               | 0.12        |

TABLE II: FAULT LOCATION ON PHASE B

| S/N | Fault Location @ Fault Resistance | Fault Location (ANFIS) | Error (ANFIS) | Fault Location (FIS) | Error (FIS) |
|-----|----------------------------------|------------------------|---------------|---------------------|-------------|
| 1   | 3.3km @ 250ohms                  | 3.29                   | 0.01          | 3.28                | 0.02        |
| 2   | 3.3km @ 300ohms                  | 3.37                   | 0.07          | 3.27                | 0.03        |
| 3   | 8.9km @ 250ohms                  | 8.96                   | 0.06          | 8.99                | 0.09        |
| 4   | 8.9km @ 300ohms                  | 8.88                   | 0.02          | 8.95                | 0.05        |
| 5   | 14.7km @ 250ohms                 | 14.70                  | 0.00          | 14.74               | 0.04        |
| 6   | 14.7km @ 300ohms                 | 14.72                  | 0.02          | 14.77               | 0.07        |
| 7   | 17.1km @ 250ohms                 | 17.12                  | 0.02          | 17.14               | 0.04        |
| 8   | 17.1km @ 300ohms                 | 17.08                  | 0.02          | 17.16               | 0.06        |

The results show that the success rate and discrimination rate of FIS are 58% and 67% respectively whereas that of ANFIS are 88.3% and 98% respectively.

In addition, using (5), it has shown that ANFIS model gives 52.12 percentage reduction in error compared with FIS for location of fault points on the case study power distribution system. This has clearly proven that ANFIS model is more effective in the classification of HIFs and location of HIF points on the distribution system.

Finally, performance evaluation was conducted on the developed models, that is, ANFIS with FIS and the results from the two methods were compared. The results show clearly that ANFIS performs better in classification and location of high impedance faults points. The work has achieved the overall objective which is to develop a model with enhanced performance in classification and location of HIFs on the 33kV power distribution.

IV. CONCLUSION

The study was conducted using FIS and ANFIS methods on two different phases of the distribution system. The case study distribution system was simulated and the results of the two methods are stated in Table I and Table II. The results show a significant difference between the error using FIS and the error using ANFIS in the classification and location of HIF on the distribution system.

Finally, using (5), it has shown that ANFIS model gives 52.12 percentage reduction in error compared with FIS in the location of HIF points along the distribution system. This has distinctively shown that ANFIS model is better than FIS in the classification and location of HIF points in the distribution system.

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