Development Of Fussy Logic Approach For Fault Current Diagnosis And Classification In Power Lines

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***Abstract*— In this paper, the development of fussy logic-based approach for fault current diagnosis and classification in power lines is presented. The essence of the study is to use some sets of input data collected over time from the case study power line to design a fussy logic that can detect when fault current fault has occurred and also determine the type of fault current that has occurred. The data used are obtained from the Transmission Company of Nigeria (TCN), Eket transmission station, Akwa Ibom State. Particularly, the absolute values of the three phase currents for each fault condition are used to calculate the values of the inputs variables to the fussy logic-based fault current diagnosis and classification system. The system is modeled in Mathlab software for a radial power network. The simulation was carried for line-A to ground (a-g), line-B to ground (b-g), line-C to ground (c-g), lines-AB to ground (a-b-g), lines-BC to ground (b-c-g), lines-CA to ground (c-a-g). Lines-AB (a-b), lines-BA (b-c), lines-CA (c-a), and lines ABC. The fussy logic-based fault diagnostic system was able to simulate and identify the ten types of power line faults. The results from the automated fussy logic-based mechanism were validated by the manually computed values for the fault current detection and classification. The results obtained using the automated fussy logic-based mechanism matched exactly with those obtained when the manual approach was used. In all, the fussy mechanism can effectively be used to detect and classify fault current that do occur in power lines.**

Keywords*— *Fault Location, Circuit Breakers, Power System Networks, Fuzzy Logic, Relays

1. Introduction

Generally, in large power system networks, large amount of data is usually collected from the transmission lines so as to implement power system control [1,2,3,4,5]. Among other things, power system control is essential for protection of the whole system and this requires real-time and accurate detection and classification of fault on the transmission lines [6,7,8,9,10]. Requisite mathematics models and attendant computer programs and process are usually put in place to enable the power system operators to detect and classify the faults and also to speed up the location and isolation of fault sections in the transmission system when fault occurs. The common procedure used for the fault diagnosis is usually based on a preset threshold for the fault current and voltages [11,12,13]. This is because faults on transmission line give rise to transient DC offset as well as high-frequency transient components which can be extracted from the fault current and voltage signals [14,15,16]. In any case, it is difficult to set a general threshold value since the fault current and voltage signal vary with different fault type, fault size and fault location, among other factors [17,18,19,20].

Furthermore, when fault occurs on a given phase of a three phase transmission line, due to the coupling effect, the faulted phase will also affect the other phases [21,22,23]. In all, it requires an intelligent approach which can use the available information on the fault current and voltages to effectively detect and classify the fault. In this paper, a fussy logic approach for fault current diagnosis and classification in power lines. In the fussy logic-based approach, different levels of fault currents and different fault conditions on the power lines are classified into various degrees of membership functions which are then used to detect and classify the fault for further effective fault location procedure. Sample transmission networks are modeled and used a case study to demonstrate the applicability of the ideas presented in this paper.

2.0 Methodology

2.1 Fuzzy Logic Algorithm (FLA) for Fault Current Diagnosis

In this work, fuzzy controller architecture is developed as shown in Figure 1. The fuzzy controller is made up of three basic elements: Fuzzification, fuzzy inference and defuzzification. In Figure 1, the input quantity is represented by X, and it represents the three phase current magnitude and zero sequence components of fault current in a crisp form. By fuzzification the input current is converted to fuzzy variables, before it is applied to the fuzzy inference engine, while the calculated degrees of the membership function are sent to the rule layer according to if–then rules. The fuzzified inputs at point “Y” are given to the fuzzy inference engine which now follows the fuzzy rule base and produces an aggregated fuzzy output; Z is the aggregated fuzzy output which serves as input to the defuzzifier. The defuzzifier combines the information in the fuzzy inputs to obtain a single crisp (non-fuzzy) output.

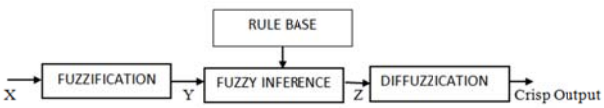

Figure 1: The fuzzy controller architecture.

2.2 Formulation of the Membership Functions

Different levels of fault currents and different fault conditions on the power lines are classified into various degrees of membership functions, namely, Low (L), Medium (M), and High (H). In this study, the values of line currents for different fault conditions which are denoted as m_1, m_2, and m_3 are given as follows;

$$\left.\begin{aligned} m_1 &= \frac{\mathrm{Abs}(I_a)-\mathrm{Abs}(I_b)}{\max(I_a,I_b,I_c)} \\ m_2 &= \frac{\mathrm{Abs}(I_b)-\mathrm{Abs}(I_c)}{\max(I_a,I_b,I_c)} \\ m_3 &= \frac{\mathrm{Abs}(I_c)-\mathrm{Abs}(I_a)}{\max(I_a,I_b,I_c)} \end{aligned}\right\} \quad (1)$$

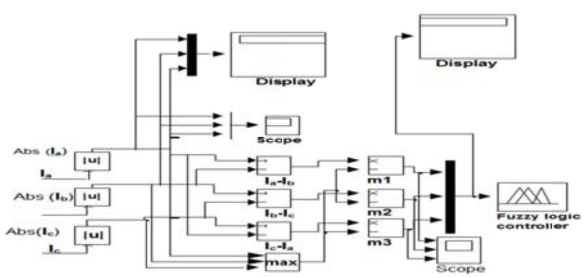

Figure 2 : Logical model for evaluating Equation (1)

Where Abs(I_a), Abs(I_b),and Abs(I_c) are the absolute values of the three phase current. The values of m_1, m_2, and m_3 for different fault conditions are used to determine the membership function for a given fault type. For fast evaluation of Equation (1), a logical model shown in Figure 2 was developed for the simulation.

2.3 Line Model for the Simulation

Variation in fault location, power angle, fault inception angle and fault resistance are very important in order to study the values of m1, m2, and m3, for any kind of fault condition [24]. The study considered a model of the secondary transmission and primary distribution network which consist of the medium voltage (MV) and low voltage (LV) lines. The radial distribution line model in Figure 3 is used to represent the power distribution system, where Vs is the sending end voltage, Vr is the receiving end current, R is the line resistance and L is the line inductance

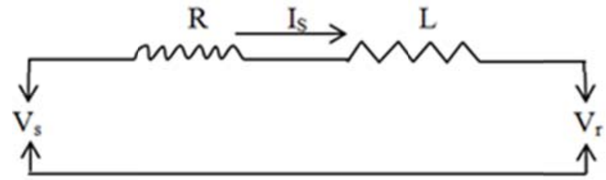

Figure 3: Radial distribution line model

2.4 The Test System Model

The accuracy and performance of the fuzzy logic-based fault current diagnostic system as described in this work is validated based on the test radial system on which the fault simulation was performed. The model is tested on the radial transmission/distribution network of Power Holding Company of Nigeria (PHCN) Plc, Eket transmission control center. The network consists of 132/33kV 45 MVA, 132/33 kV 60 MVA, and 33/11 kv 15 MVA power transformers. The positive, negative and zero sequence components required in building the logical model of the test system for simulation are given in terms of the line reactance (R), inductance (L) and capacitance (L) which are given as follows: R+ = R- = 0.1579 Ω/km , L+ = L- =0.011 H/km andC+ = C- = 5.681F/km. The single line diagram of the radial power network used as test system is shown in Figure 4.

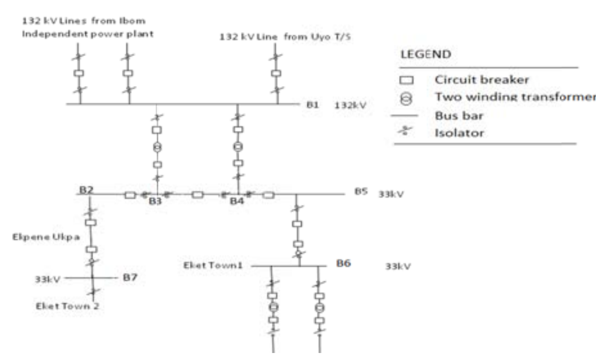

Figure 4: Single line representation of the radial power network

2.5: The Simulation Model

The system simulation model was performed using the MATLAB/Simulink software version 7.7. The simulations for the various types of faults current were performed and the various values for both faulted and non-faulted current were taken and recorded. Figures 5, Figure 6, Figure 7, Figure 8 and Figure 9 show the logical block dialogue boxes which were used in building the logical model in Simulink for the fault current detection and diagnosis. The Simulink model parameters for the three phase power source for the radial distribution system is shown in Figure 5 . In the transformer block shown in Figure 6, the required parameters of the two winding transformer were specified. This block represents a real step down transformer on the distribution network with parameters set to per unit values.

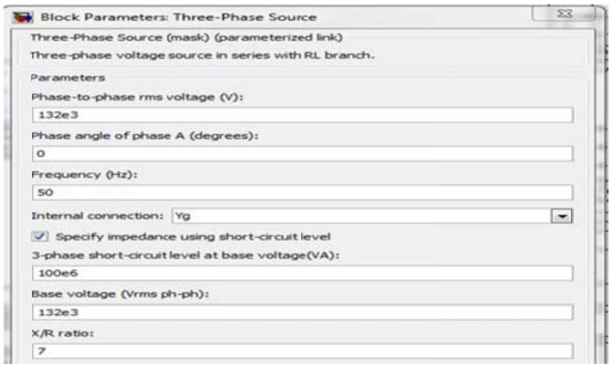

Figure 5: The Simulink model parameters for the three phase power source

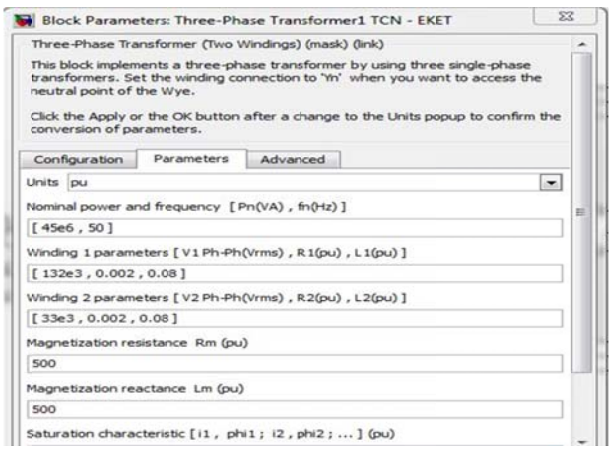

Figure 6: The Simulink model parameters for the transformer block

In this study, the distributed parameter block was set to implement a three phase distributed line model as shown in Figure 7. The three phase series load was implemented on the simulation model as shown in Figure 8. The three phase load is either purely resistive or inductive. It is used to implement a fault between any phase and the ground. The fault timing was defined directly from the dialog box. The parameter for the fault implementation block is as shown in Figure 9.

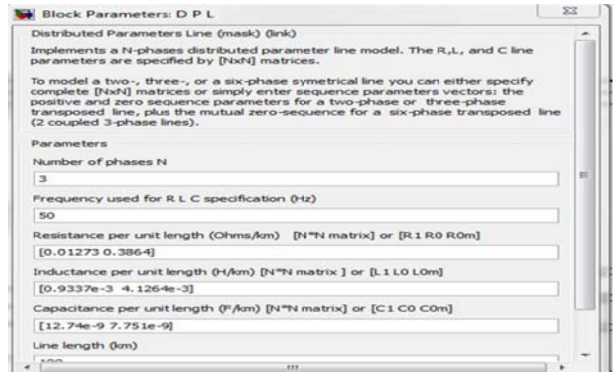

Figure 7: The Simulink model parameters for the distributed parameters line block

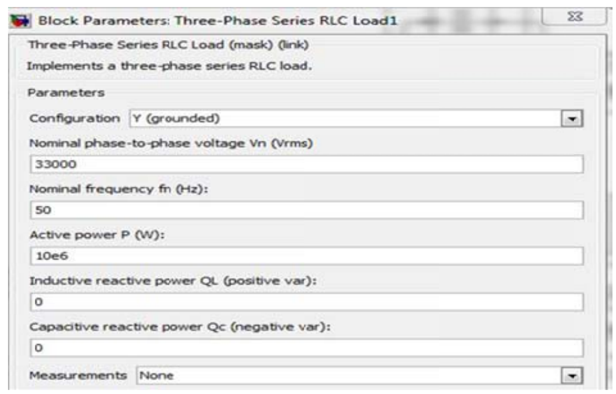

Fig. 8: The Simulink model parameters for the three phase series load.

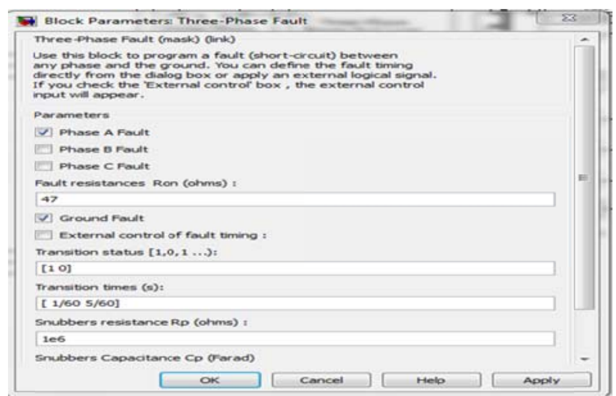

Figure 9: Three phase fault implementation block.

In addition to the above mentioned logical blocks, other blocks such as circuit breakers, absolute value computation, interval test, display, scope block, and measurement blocks were also used in building the logical model for simulation MATLAB 7.7.

To ascertain the accuracy of the logical model in Figure 2 which is an integral part of the simulation model in evaluating Equation (1), the three line currents (I_a, I_b and I_c) were measured for every fault condition. The values of I_a, I_b and I_c obtained for each fault condition were used to evaluate Equation (1) manually for corresponding values of m_1, m_2 and m_3 and then compared to the output of the logical model.

For the sake of manual calculations the values of I_a, I_b and I_c obtained for each fault condition as simulated are given in Table 1.

Table 1 : Absolute values of I_a, I_b and I_c for each fault condition.

Fault type	Abs(I_a) (A)	Abs(I_b) (A)	Abs (I_c) (A)
a-g	1.504	0.1126	0.00414
b-g	0.01646	0.4454	0.00017
c-g	0.0144	0.01064	3.722
a-b-g	0.1966	0.08595	0.00745
b-c-g	0.01764	3.563	8.28
c-a-g	0.4624	0.00988	8.288
a-b	0.3041	0.298	0.01105
b-c	0.01781	0.5543	0.5263
c-a	1.082	0.01895	1.063
a-b-c	1.212	0.2952	0.9149

From Table 1 and Equation (1), the values of m_1, m_2 and m_3 were evaluated for phase A-to-ground (a-g) fault condition as follows;

$m_1 = \frac{1.504-0.1126}{1.504}$ = 0.9925; $m_2 = \frac{0,1126-0.00414}{1.504}$ = 0.004735 and $m_3 = \frac{0.00414-1.504}{1.504}$ -0.9972

For phase B-to-ground (b-g) fault, Equation (1) is evaluated as follows;

$m_1 = \frac{0.01646-0.4454}{0.4454}$ = -0.963; $m_2 = \frac{0.4454-0.00017}{0,4454}$ = 0.9996 and $m_3 = \frac{0,00017-0.01646}{0.4454} = -0.03657$

Similarly, Equation (1) was used to the values of m_1, m_2 and $m_3$for each of the fault conditions as and the values obtained are represented in Table 2.

Table 2 Calculated values of inputs m_1, m_2, and m_3.

Fault type	m_1	m_2	m_3
a-g	0.9925	0.00474	-0.9972
b-g	-0.963	0.9996	-0.03657
c-g	0.00101	-0.9971	0.9961
a-b-g	0.5629	0.3992	-0.9612
b-c-g	-0.4281	-0.5698	0.9979
c-a-g	0.05459	-0.9988	0.9442
a-b	0.02007	0.9436	-0.9637
b-c	-0.9679	0.05042	0.9174
c-a	0.9825	-0.9652	-0.01727
a-b-c	0.7564	-0.5114	-0.245

In order to apply the fussy logic method for the fault diagnosis, the values of the inputs m_1, m_2, and m_3 for each fault type are classified into various degrees of membership functions – Low (L), Medium (M), and High (H). The values of m_1, m_2, and m_3 are between -1 and 1. In order to know the range at which each input belongs to a given membership function, values of m_1, m_2, and m_3 for all fault type were arranged in ascending order and in a single column. For m_1, m_2 and m_3, "Low" means a value between -1 and -0.2; "medium" means a value between -0.65 and 0.37 and "high" means a value between 0.2 and 1. Therefore, from Table 2 the input variable type that indicates the nature of fault is obtained by applying the simple if–then rules listed in Table 3.

Table 3: The membership function of the input variable

IF			THEN
m_1	**m_2**	**m_3**	**Fault Type**
High	Medium	Low	a-g
Low	High	Medium	b-g
Medium	Low	High	c-g
High	Medium	Low	a-b-g
Low	Medium	High	b-c-g
Medium	Low	High	c-a-g
Medium	High	Low	a-b
Low	Medium	High	b-c
High	Low	Medium	c-a
High	Low	Low	a-b-

For Line A-to-ground (a-g) fault the rule based on Table 3 is read as follow;

If m_1 is high and m_2 is medium and m_3 is low then fault type is a-g.

The membership functions of the input variable are keyed into the fuzzy inference system (FIS) through the membership function editor as shown in Figure 10. The membership function of the output variable (fault type) is also keyed in as shown in Figure 11. The rules on Table 3 are implemented in the fuzzy rule editor as shown in Figure 12.

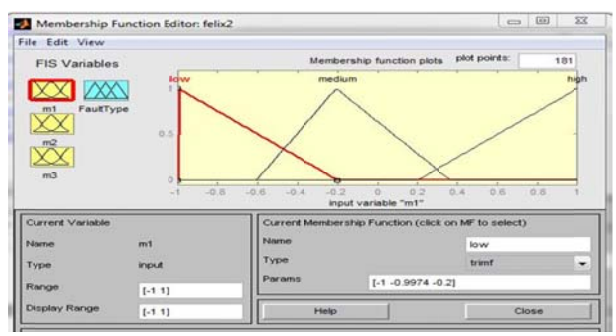

Figure 10: Membership function plots for input variables m_1, m_2, and m_3

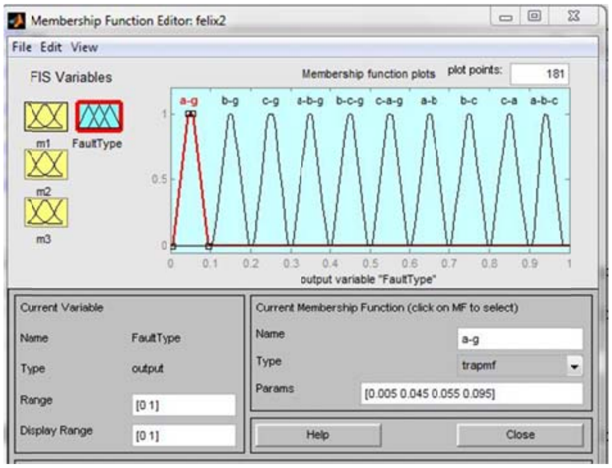

Figure 11: Membership function plots for input variables m_1, m_2, and m_3

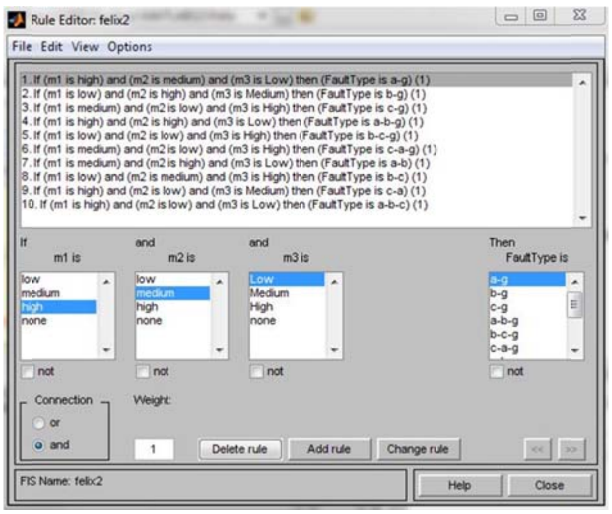

Figure 12: Fuzzy logic rule editor

The highlighted rule in Figure 12 is read as follow:

If m_1 is high and m_2 is medium and m_3 is low then fault type is a-g.

The fuzzy rule is housed by the fuzzy logic controller block in the simulation model shown in Figure 12. The simulation was performed for all the fault conditions and the results are presented in the result and discussion section.

3 Results and discussion

3.1 The simulation results for the values of m_1, m_2 and m_3

Figure 13 shows part of the simulation model of the subsystem used for automatic calculation of the corresponding values of the fuzzy logic's input variables m_1, m_2 and m_3 for every value of I_a, I_b and I_c. The simulation was carried out for ten different types of faults and the values of m_1, m_2 and m_3 generated automatically for every fault type are presented in Table 4.

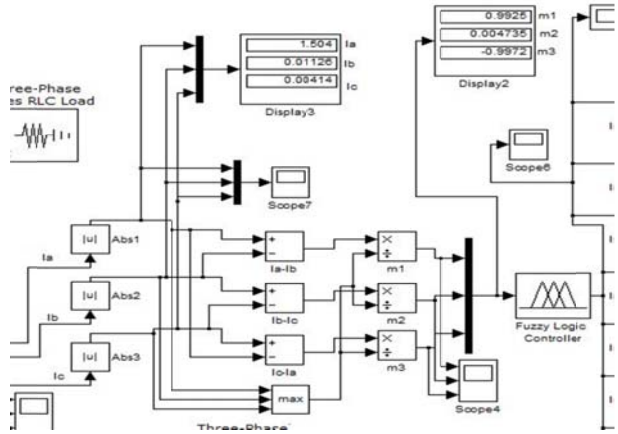

Figure 13: The Simulink model of the subsystem that displays the values of m_1, m_2 and m_3 for every value of I_a, I_b and I_c.

Table 4: Automatically generated values of m_1, m_2, and m_3 based on the Simulink model of Figure 14

Fault type	m_1	m_2	m_3
a-g	0.9925	0.00473	-0.9972
b-g	-0.963	0.9996	-0.03657
c-g	0.00101	-0.9971	0.9961
a-b-g	0.5629	0.3992	-0.9612
b-c-g	-0.4281	-0.5698	0.9979
c-a-g	0.05459	-0.9988	0.9442
a-b	0.02007	0.9436	-0.9637
b-c	-0.9679	0.05042	0.9174
c-a	0.9825	-0.9652	-0.01727
a-b-c	0.7564	-0.5114	-0.245

3.2 Comparison of manually and automatically Generated Values of m_1, m_2 and m_3

The comparison of Table 1 (which is the manually calculated values of m_1, m_2 and m_3) and Table 4 (which is the automatically generated values of m_1, m_2 and m_3 based on the Simulink model of Figure 14) shows that the manually and the automatically generated values of the fuzzy logic input variables (m_1, m_2 and m_3) are the same. This validates the accuracy of the logical model (Figure 14) used for evaluating Equation (1).

$$m_1 = \frac{\mathrm{Abs}(I_a) - \mathrm{Abs}(I_b)}{\max(I_a, I_b, I_c)} \;;\quad m_2 = \frac{\mathrm{Abs}(I_b) - \mathrm{Abs}(I_c)}{\max(I_a, I_b, I_c)} \;;\quad m_3 = \frac{\mathrm{Abs}(I_c) - \mathrm{Abs}(I_a)}{\max(I_a, I_b, I_c)} \;;$$

3.3 Results of the simulations of the fuzzy logic-based fault current detection and diagnosis

During the simulation, fuzzy logic input variable (m_1, m_2 and m_3) were automatically fed into the fuzzy logic controller which made use of the rules on Table 3 to display output values between 0 and 1 corresponding to the type of fault detected in the system. Figure 14 shows part of the simulation model which displayed an output value of 0.05

Journal of Multidisciplinary Engineering Science Studies (JMESS)
ISSN: 2458-925X
Vol. 8 Issue 1, January - 2022

corresponding to line-A to ground (a-g) fault. The first interval test block (interval test1) attached to the output of the fuzzy logic controller in Figure 14 displayed TRUE (1) for line-A to ground (a-g) fault while every other interval test block displayed FALSE (0) as the output value of 0.05 was not within their respective interval of output value.

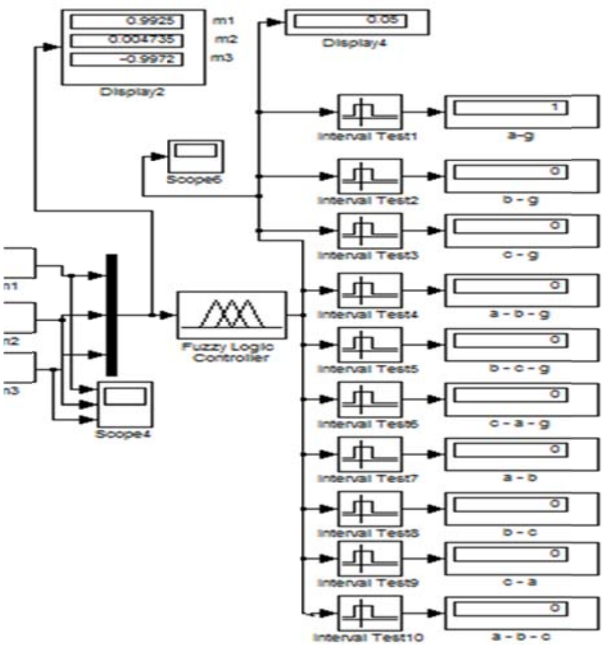

Figure 14: Fault detection and diagnosis by fuzzy logic controller.

The simulation was carried for line-A to ground (a-g), line-B to ground (b-g), line-C to ground (c-g), lines-AB to ground (a-b-g), lines-BC to ground (b-c-g), lines-CA to ground (c-a-g). Lines-AB (a-b), lines-BA (b-c), lines-CA (c-a), and lines ABC. The fault diagnostic system was able to simulate and identify the ten types of power line faults. Some of the faults detected as viewed by the scope-3 and scope-6 in the simulation model are shown in Figure 15 to Figure 22. It can be seen on Figure 15 that the fuzzy logic output of 0.05 is within the range of 0 and 0.1 which corresponds to the range of output variable for Line A-to-ground fault (a-g)as shown on Figure 14.

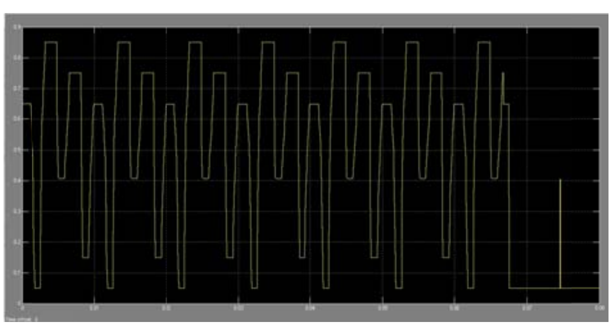

Figure 15: Fuzzy logic crisp output (0.05) for line A-ground fault (a-g)

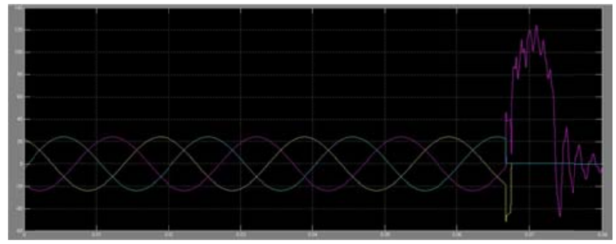

Figure 16. Line A-to-ground fault (a-g)

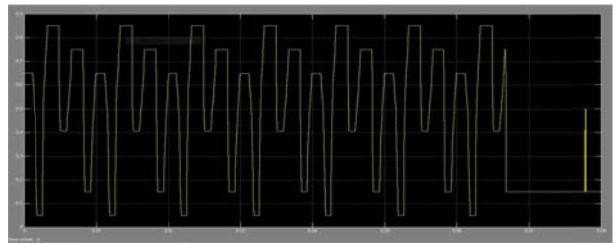

Figure 17. Fuzzy logic crisp output (0.15) for line B-to-ground fault (b-g)

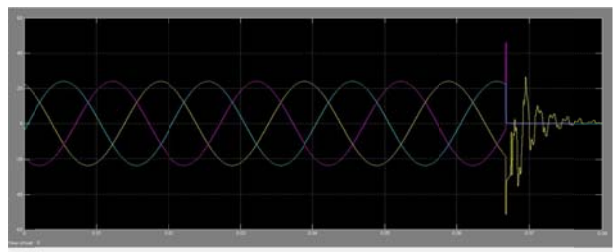

Figure 18. Line B-to-ground fault (b-g)

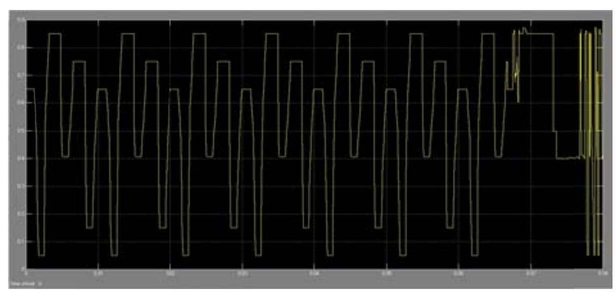

Figure 19. Fuzzy logic crisp output (0.4059) for lines A-C-to-ground fault (a-c-g)

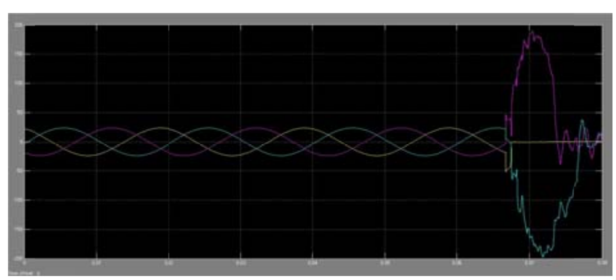

Figure 20. Lines A-C-to-ground fault (a-c-g)

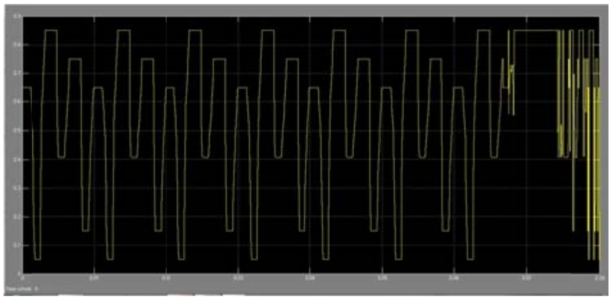

Figure 21. Fuzzy logic crisp output for lines A-B-C fault (a-b-c)

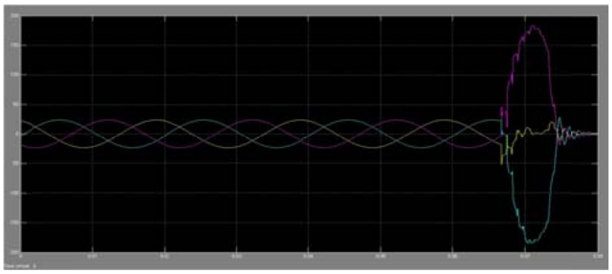

Figure 22. Lines A-B-C fault (a-b-c)

4 Conclusion

Fault current detection and classification in power system networks is presented. In the study , the absolute values of the three phase currents for each fault condition are used to calculate the values of the inputs variables to the fussy logic-based mechanism that can detect when fault current fault has occurred and also determine the type of fault current that has occurred. Data obtained from the Transmission Company of Nigeria (TCN), Eket transmission station, Akwa Ibom State were used in the study. Different fault types were modeled and simulated in Mathlab software for a radial power network. In all, the fussy logic-based fault diagnostic system was able to simulate and identify the different types of power line faults in the model.

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