Transmission Lines Fault Classification and Location via Fuzzy-ANFIS Technique

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***Abstract*— A fault in a transmission line may cause power system interruption as well as lead to severe damages on system equipment. This paper presents a fault classification and location via Fuzzy Logic System and ANFIS respectively. A single-ended transmission line model was developed to obtain the value of fault current and fault voltage. Classification of transmission line fault was developed by using fuzzy logic that use the faults data at one-end of the transmission line and while the same data was used to train ANFIS for fault location. To illustrate the effectiveness of the proposed method, an extensive simulation by using MATLAB Simulink have been carried out for various types of fault includes Single Line-to-Ground, Double Line-to-Ground, Line-to-Line and three phase fault. The manual calculation also has been performed for the Single Line-to-Ground fault to compare the simulation results.**

***Index Terms*—ANFIS, Fuzzy Logic, Fault classification, Fault location**

I. Introduction

Transmission lines normally constructed in an open area make it very vulnerable to the outside world and highly exposed to the fault occurrence [1]. A fault in a transmission line may lead to the disturbance in the system as well as can cause severe damages on system equipment [2]. These faults are quite impossible to be avoided since there is a small part of these faults also occur because of the natural phenomenon and far beyond the human control [3]. The fault also may happen at various random locations and the power of the transmission line will degrade. Thus, in order to keep the power continuity of the transmission maintained, it is very necessary to detect and locate the fault's location immediate and precisely in order to isolate those sections of the system [4].

II. Literature Review

A. Introduction

The accurate and fast fault location technique can accelerate the system restoration, reducing outage time and improving system reliability [5,6]. The engineers intend to have such a technique that can help them to find the accurate fault location as it can help to restore the power service to the consumers in a shorter time [7]. In this chapter, the research pertaining to the fault location techniques in power transmission lines was reviewed.

B. Simple Reactance Method

In this method, as conducted by Zimmerman and Costello [8], the authors used the value of voltage and current at the terminal during fault as shown in Figure 1. The other main parameter that should be determined is the line impedance per unit length and the fault location can be calculated.

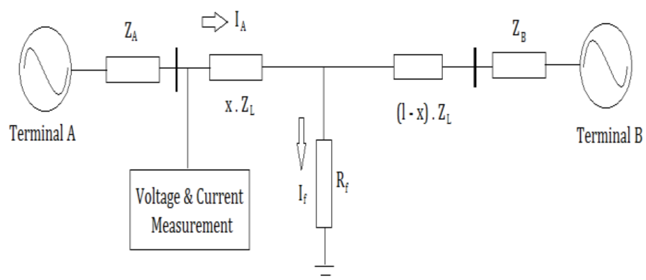

Fig. 1. Faulted Transmission Line

From [8], once Kirchhoff Voltage Law from the voltage measurement to the fault applied, the voltage measured is given by [18]

$$V_A = I_A.X.Z_L + I_f.R_f$$

Where,

V_A : Voltage terminal at A,
X : Distance from the terminal A to the fault,
I_A : Current flows in the transmission line,
Z_L : Transmission line impedance,
R_f : Fault resistance
I_f : Fault current.

By rearranging equation above, the fault location is given by [8]

$$x = \frac{V_A/I_A}{Z_L} - \frac{R_f}{Z_L\left(I_A/I_f\right)}$$

C. Travelling Wave Method

Travelling wave technique considered the speed of light in the current and voltage signals that travel from the terminal to the fault location [9]. The studies in [2] presented a fault location using high frequency travelling wave. It is basically based on the correlation between the forward and backward travelled waves in the lines. The main objective is to detect the high-frequency travelling waves that initiated by fault at the fault location [3].

D. Takagi Method

Takagi method [10] is a simple and innovative method developed by Toshio Takagi in 1982. This method basically is an enhancement of the simple resistance method by taking out the load current from the total fault current. Fault network is decomposed into a pre-fault and fault network by using the superposition principle.

E. Artificial Intelligence Method

Artificial Neural-Network and Fuzzy Logic approach are one of the latest development made for fault classification as well as fault location recently. The paper [11] conducted by Uzubi, Ekwue and Ejiogu about a fault location technique via ANN by using feed-forward and backpropagation training algorithm to detect a fault in the Nigerian 132 kV transmission line. The researched proved that the ANN has the ability to locate the fault with high precision.

In addition, Meyur [12] proposed and validates a fault locating methodology by using hybrid consist of wavelet and ANFIS on a two bus parallel transmission system by using MATLAB. The authors used Multi-resolution analysis (MRA) technique in Discrete Wavelet Transform (DWT) to extract details regarding fault location estimation. The extracted the harmonic features from fault signal was used as input of ANFIS to locate the fault.

F. Summary

In conclusion, there are many techniques have been proposed to identify, classify as well as locate the fault. The fact that every single method has their owned advantages and disadvantages cannot be denied and this situation lead to many hybrid techniques have been developed to achieve the desired performance. In this study, a combination of Fuzzy Logic System and ANFIS was employed to classify and locate the fault in a transmission line respectively. A Single-Ended 300 km transmission line was modelled to be used in this study.

III. Methodology

A. General

The fault classification and location method has been developed on the extensive simulation by using MATLAB Simulink have been carried out for various types of fault includes Single Line-to-Ground, Double Line-to-Ground, Line-to-Line and three phase fault. In this work, Fuzzy Logic System and ANFIS approach employed as a method to classify and locate faults in the transmission lines. The 300 km Single-Ended Series transmission line model was created by using Simulink MATLAB to produce the fault signals to the systems. In fault classification, post-fault data extracted and be used to create fuzzy rules. The same fault signal also then be injected to the ANFIS toolbox in order to obtain the fault location of the faults. All the parameters of the power system model of Figure 2 are as follows [13]:

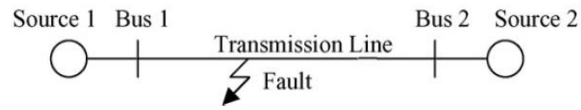

Fig. 2. The power system model

- Line length : 300 km
- Source 1 and Source 2
  - Voltage : 400 kV
  - Resistance : 1.31 Ω
  - Inductance : 0.0477 H
- Frequency : 50 Hz
- Transmission line
  - Positive sequence : 0.0275 + j0.3142 Ω/km
  - Negative Sequence : 0.275 + 1.0267 Ω/km

B. Fault Classification via Fuzzy Logic System

Post-fault data of three phase current, obtained from the power system model via Simulink are considered for fault classification. Hence, all these data will be transferred to the MATLAB to classify the fault type. The characteristic features of various types of fault can be analysed in term of Δ_1, Δ_2 and Δ_3 which are calculated as follows [14];

- Fault ratios

$$r_1 = \frac{\max[abs(I_a)]}{\max[abs(I_b)]}, \quad r_2 = \frac{\max[abs(I_b)]}{\max[abs(I_c)]},$$

$$r_3 = \frac{\max[abs(I_c)]}{\max[abs(I_a)]}$$

Where I_a, I_b and I_c are the post-fault samples of three-phase currents.

- Normalized value of r1, r2 and r3 are [14];

$$r_{1n} = \frac{r_1}{\max(r_1, r_2, r_3)}, \quad r_{2n} = \frac{r_2}{\max(r_1, r_2, r_3)},$$

$$r_{3n} = \frac{r_3}{\max(r_1, r_2, r_3)}$$

- The difference of the normalized values given by [14];

$\Delta_1 = r_{1n} - r_{2n}$, $\Delta_2 = r_{2n} - r_{3n}$, $\Delta_3 = r_{3n} - r_{1n}$

As mentioned before, Δ_1, Δ_2 and Δ_3 represent the characteristic features of various types of fault. Hence, the fuzzy rule was created for fault classification by using these characteristic features.

For various types of faults, which is a-g, a-b-g, a-b and a-b-c-g, the values of Δ_1, Δ_2 and Δ_3 for various fault location are shown in Tables 1-4. The other value of line-to-ground, line-line and line-to-line-to-ground also has been observed in order to create the fuzzy rules.

Table 1
Values of Δ_1, Δ_2 and Δ_3 for a-g fault under variable fault location

Fault Location(km)	Δ_1	Δ_2	Δ_3
45	0.9958	0.0042	-1
60	0.9592	0.0392	-0.9984
120	0.9574	0.0409	-0.9983
200	0.9757	0.0238	-0.9995

From the value of Δ_1, Δ_2 and Δ_3 for line-to-ground fault, it can be illustrated as follows;

- a-g fault : Δ_1 = high, Δ_2 = medium, Δ_3 = low
- b-g fault : Δ_1 = low, Δ_2 = high, Δ_3 = medium
- c-g fault : Δ_1 = medium, Δ_2 = low, Δ_3 = high
- a-b-g fault : Δ_1 = low, Δ_2 = high, Δ_3 = low
- b-c-g fault : Δ_1 = low, Δ_2 = low, Δ_3 = high
- c-a-g fault : Δ_1 = high, Δ_2 = low, Δ_3 = low

where high indicates a value between 0.4 until 1, medium indicates a value between -0.02 until 0.5 and low indicates the value between -1 until -0.005.

Table 2
Values of Δ_1, Δ_2 and Δ_3 for a-b-g fault under variable fault location

Fault Location(pu)	Δ_1	Δ_2	Δ_3
45	-0.9468	0.9994	-0.0526
60	-0.9477	0.9994	-0.0517
120	-0.9454	0.9992	-0.0538
200	-0.9528	0.9994	-0.0465

From the value of Δ_1, Δ_2 and Δ_3 for faults involving ground, it can be illustrated as follows;

Table 3
Values of Δ_1, Δ_2 and Δ_3 for a-b fault under variable fault location

Fault Location(pu)	Δ_1	Δ_2	Δ_3
45	-0.9877	0.9998	-0.0122
60	-0.9857	0.9998	-0.0141
120	-0.9780	0.9995	-0.0215
200	-0.9678	0.9988	-0.0311

Table 4
Values of Δ_1, Δ_2 and Δ_3 for a-b-c fault under variable fault location

Fault Location(pu)	Δ_1	Δ_2	Δ_3
45	0.9958	0.0042	-1
60	0.6709	0.0837	-0.7546
120	0.6686	0.0857	-0.7543
200	0.6578	0.0960	-0.7538

From the value of Δ_1, Δ_2 and Δ_3 for faults not involving ground, it can be illustrated as follows;

- a-b fault : Δ_1 = low, Δ_2 = high, Δ_3 = low
- b-c fault : Δ_1 = low, Δ_2 = low, Δ_3 = high
- c-a fault : Δ_1 = high, Δ_2 = low, Δ_3 = low
- a-b-c fault : Δ_1 = medium, Δ_2 = medium, Δ_3 = low
- or : Δ_1 = low, Δ_2 = medium, Δ_3 = medium
- or : Δ_1 = medium, Δ_2 = low, Δ_3 = medium
- or : Δ_1 = low, Δ_2 = low, Δ_3 = medium
- or : Δ_1 = medium, Δ_2 = low, Δ_3 = low
- or : Δ_1 = low, Δ_2 = medium, Δ_3 = low

where high indicates a value between 0.4 until 1, medium indicates a value between 0.01 until 0.5 and low indicates the value between -1 until 0.01.

As discussed in the previous section, the various types of fault can be classified by analyze the fault characteristic features, Δ_1, Δ_2 and Δ_3, which then used as the fuzzy variables. By referring to these fuzzy variables, sets of fuzzy rules were developed for classification of fault of ground and phase fault type as shown in the previous section.

Hence, a fuzzy of 3 inputs represent Δ_1, Δ_2 and Δ_3 where all the inputs contain 3 membership functions as shown in Figure 3-4.

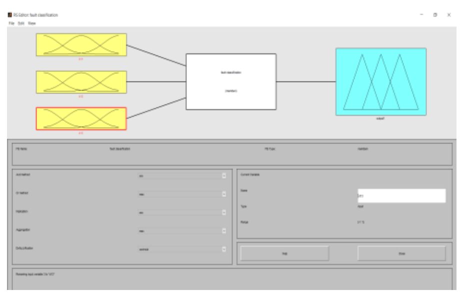

Fig. 3. Fuzzy logic system

The variables in the antecedent parts as well as the consequent parts, in the above fuzzy rules should be fuzzy variables. The triangular membership function shown in Fig. 3 has been used to represent the various fuzzy variables in the antecedent and consequent parts of the fuzzy rules. The triangular membership function can be defined with reference to the points A, B and C, called as triplets. As shown in Fig. 3, the points A and C have membership value of 0 while at point B the membership value is 1.

Table 5-6 shows the fuzzy variables in the antecedent part of selected values of triplets of the fuzzy rules for the faults involving ground and faults not involving ground respectively.

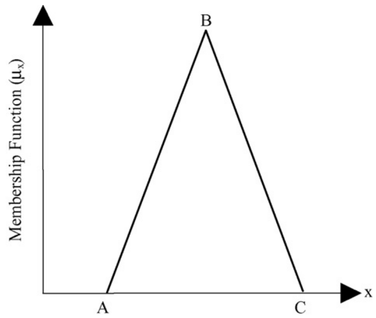

Fig. 4. The triangular fuzzy membership function

Table 5
Antecedent parts of fuzzy rules corresponding to ground faults

Fuzzy variable	A	B	C
High	0.4	0.7	1
Medium	-0.02	0.16	0.5
Low	-1	-0.5	-0.005

Table 6
Antecedent parts of fuzzy rules corresponding to phase faults

Fuzzy variable	A	B	C
High	0.4	0.7	1
Medium	0.01	0.16	0.5
Low	-1	-0.5	-0.010

Table 7
Consequence parts of fuzzy rules

Fuzzy variable	A	B	C
a-g	4.5	5	5.5
b-g	9.5	10	10.5
c-g	14.5	15	15.5
a-b-g	19.5	20	20.5
b-c-g	24.5	25	25.5
c-a-g	29.5	30	30.5
a-b	34.5	35	35.5
b-c	39.5	40	40.5
c-a	44.5	45	45.5
a-b-c	49.5	50	50.5

C. *Fault Location via Adaptive Neuro-Fuzzy Inference System (ANFIS)*

Neuro-fuzzy system basically is a combination between ANN and fuzzy system, by right using the advantages of allowing an easy translation of the final system into a set of if-then rules. ANFIS has the capability of ANN in pattern recognition and direct adaption of knowledge articulated as a set of fuzzy linguistic rules [15]. In this system least-square method as well as back-propagation gradient descent method was used for FIS membership function parameters training. Even though ANN basic is used, hybrid approach makes ANFIS space dimension reduced and hence make it converge much faster.

D. *ANFIS Architecture*

ANFIS consist of multilayer feed-forward network composed of notes that connected by directed links. Every link exists in adaptive network has their own specifies direction of signal flow from one node to another and in contrast with ANN, no weights are assigned to the link. Moreover, in the adaptive network configuration, static node function was performed on the incoming signals to generate single mode output and each node function parameters are modifiable. The overall behavior of the adaptive network will change by changing those parameters.

Figure 5 shows the basic architecture of ANFIS that consist of 5 main layers which is fuzzification, antecedent, normalized firing strength, consequent and aggregator [9]. In Layer 1, fuzzification of the input was performed based on the respective membership functions. Referring to Figure 3.1 *Ai* and B_i represent linguistic values of input x and y respectively. The given membership function of the parameters involved are called as antecedent parameters. In order to achieve minimum error, all adaptive nodes in Layer 1 will keep changing the antecedent parameter during the training process.

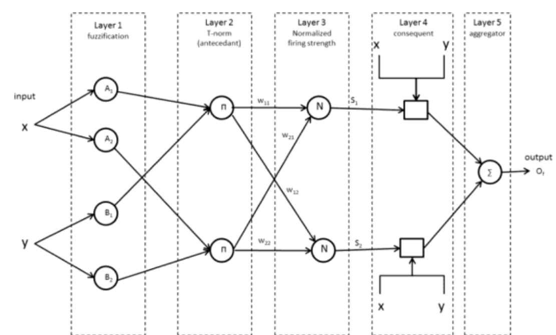

Fig. 5. Basic architecture of ANFIS

Layer 2 of the ANFIS architecture consists of the rule base with t-norm operator which is generally considered as equivalent to a product operator. Unlike nodes in Layer 1, all nodes in Layer 2 are fixed and each of the node emits firing strength (w_{li}) of the corresponding rule and can be expressed in [16] as

$$w_{li} = \prod_i^V \{\mu_A(x_i)\}$$

Where μ_A is the membership function of fuzzy set A for a linguistic variable *i* for a given rule r, by assuming the *V* is the total number of linguistic variables. The normalized firing strength in nodes in Layer 3 is given by [16]

$$S_r = \frac{w_{li}}{\sum_l^n w_{li}} = \frac{\prod_i^V \{\mu_A(x_i)\}}{\sum_l^n \prod_i^V \{\mu_A(x_i)\}}$$

l: layer number

r: number of node in given layer

n: total numbers of nodes in Layer 1

In Layer 4, consequent part of each rule based on firing strength. Sugeno architecture based is used for the ANFIS model for computing the consequent part. A first order Sugeno model computes a consequent part as follows [16]

$$O_r = S_r(a_r x + b_r y + p)$$

O_r : Output of consequent part, r

S_r : Normalized firing strength

p : Consequent parameters

In order to generate the overall output, Layer 5 will aggregate all of the individual consequent parts from the respective rules and hence will be defuzzifies [16]

$$O_f = \sum S_r f_r = \frac{\sum_r^n S_r(a_r x + b_r y + p)}{\sum_r^n S_r}$$

O_r : Output of consequent part, r

S_r : Normalized firing strength

p : Consequent parameters

E. *Proposed Method*

The basic structure of the proposed ANFIS consists of the post-fault current signal data, the hidden layer and the fault location. The system takes one input, the fault current and one output which is the fault location on the transmission line. Figure 6 shows the MATLAB ANFIS editor.

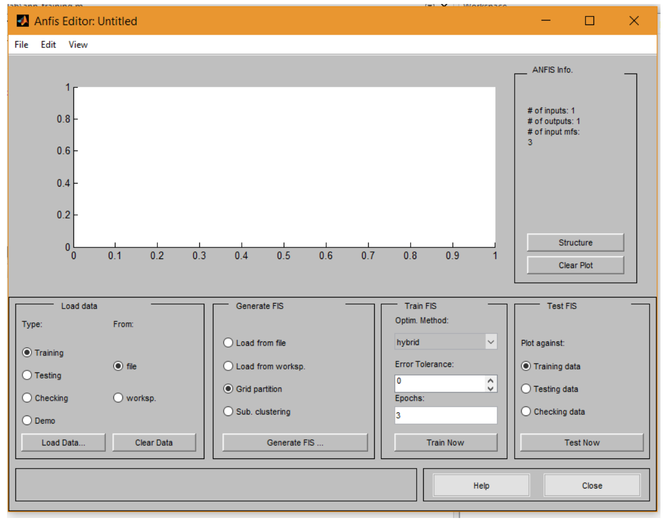

Fig. 6. MATLAB ANFIS Editor

IV. Result and Discussion

A. *Fault classification*

Now, in order to classify the faults in the transmission line, a fuzzy system was developed according to the fuzzy rules below.

For the ground fault

- a-g fault : Δ_1 = high, Δ_2 = medium, Δ_3 = low
- b-g fault : Δ_1 = low, Δ_2 = high, Δ_3 = medium
- c-g fault : Δ_1 = medium, Δ_2 = low, Δ_3 = high
- a-b-g fault : Δ_1 = low, Δ_2 = high, Δ_3 = low
- b-c-g fault : Δ_1 = low, Δ_2 = low, Δ_3 = high
- c-a-g fault : Δ_1 = high, Δ_2 = low, Δ_3 = low

For the phase fault

- a-b fault : Δ_1 = low, Δ_2 = high, Δ_3 = low
- b-c fault : Δ_1 = low, Δ_2 = low, Δ_3 = high
- c-a fault : Δ_1 = high, Δ_2 = low, Δ_3 = low
- a-b-c fault : Δ_1 = medium, Δ_2 = medium, Δ_3 = low
- or : Δ_1 = low, Δ_2 = medium, Δ_3 = medium
- or : Δ_1 = medium, Δ_2 = low, Δ_3 = medium
- or : Δ_1 = low, Δ_2 = low, Δ_3 = medium
- or : Δ_1 = medium, Δ_2 = low, Δ_3 = low
- or : Δ_1 = low, Δ_2 = medium, Δ_3 = low

In order to test the performance of the proposed method for the classification of fault, a 400kV, 3 phase, 300 km single-ended transmission line was simulated. Then, all the data obtained as shown in Table 8-9 will be used as antecedent part for the FLS. Two similar Sugeno fuzzy systems consist of three inputs and one output with triangular membership functions was designed to develop FLS.

Table 8

Antecedent parts of fuzzy rules corresponding to ground faults

Fuzzy variable	A	B	C
High	0.4	0.7	1
Medium	-0.002	0.16	0.5
Low	-1.1	-0.5	-0.002

Table 9
Antecedent parts of fuzzy rules corresponding to phase faults

Fuzzy variable	A	B	C
High	0.4	0.7	1
Medium	0.01	0.16	0.5
Low	-1.1	-0.5	-0.01

The fault classification method proposed in this paper and the method proposed by Das [10] are similar in the sense that both are fuzzy logic based schemes which require the consideration of the post-fault samples of three phase currents at the relay location. Further, the same network configuration has been considered for simulation study of both the methods.

The validity of the proposed method has been tested in case of the developed single-ended transmission line model and the FLS input for fault classification as shown in Table 10-11.

The proposed method is applicable for a wider variation in the operating conditions in comparison to the method proposed by Das [10]. Whereas the transmission line parameter is valid for variation in R_F up to 10 Ω and variation in d up to 230 km.

Table 10
FIS output for ground fault

Fault type	Fault condition d(km), Rf(Ω)	FIS Output
a-g	150,0.001	5.1
b-g	70,0.01	9.9
c-g	230,0.1	15
a-b-g	50,10	20.1
b-c-g	230,0.01	24.9
c-a-g	150,0.001	29.8

Table 11
FIS output for phase fault

Fault type	Fault condition d(km), Rf(Ω)	FIS Output
a-b	150,0.001	35.1
b-c	70,0.01	39.9
c-a	230,0.1	45
a-b-c	50,0.001	50

B. Fault Location

ANFIS graphic user interface was used to obtain the fault location. The fault current value will be transferred to the ANFIS toolbox to identify the location of the fault. In order to test the accuracy of the system, all the results will be tested by using equation below and Table 12-15 are the results of the simulation of ANFIS detecting location of various types of fault. The ANFIS had been trained with some value of training data in order to determine its performance for locating faults.

$$\%\,Error = \frac{(Actual\ distance - Calculated\ distance)}{Actual\ distance} \times 100$$

Table 12
ANFIS output for SLG fault

Actual Distance	Estimated	Difference	Error
40	40	0	0
62	61.5	0.5	0.8
127	127	0	0
173	172	1	0.5
255	256	1	-1.17

Table 13
ANFIS output for DLG fault

Actual Distance	Estimated	Difference	Error
40	40	0	0
62	62.3	0.3	-0.48
127	128	1	-0.79
173	172	1	0.59
255	254	1	0.39

Table 14
ANFIS output for LL fault

Actual Distance	Estimated	Difference	Error
40	40	0	0
62	63.3	1.3	-2.1
127	127	0	0
173	172	1	0.6
255	251	4	1.6

Table 15
ANFIS output for symmetrical fault

Actual Distance	Estimated	Difference	Error
40	40	0	0
62	61.5	0.5	0.8
127	127	0	0
173	172	1	0.5

According to Table 12-15, it is observed that the difference between the actual location of faults and the simulated values are around 0 km to 4km. In a perspective of percentage error, the error is big at the first km while at others kilometers the error due to the distance is smaller. However, whenever the big error occurs, it will affect the overall percentage error of the system. This is mainly because of the training data set used while developing the ANFIS.

Furthermore, the proposed method is computationally simpler as it requires the computation of post-fault current samples and post-fault voltage samples for determining the fault location. ANFIS can be re-trained if there are any changes of transmission line parameter includes fault inception angle and fault resistance while ANFIS developed in this report emphasize on the fault location only.

V. Conclusion

Fault occurrence in the transmission line needs to be seriously monitored in order to save all the equipment damage caused by fault. Hence, the main aim of this study is to classify the fault and hence estimate the fault location based on FLS and ANFIS technique. The performance of the developed FLS and ANFIS was assessed to prove that it is accurate enough to be used in fault monitoring system for the transmission line.

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