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Fuzzy Logic based Fault Classifier for Protection of Transmission Line using Current Samples and Angular Differences

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Abstract: Fault classification technique for transmission line protection is suggested in this paper by Fuzzy logic. Proposed fault classification methodology requires three phase post fault current samples at one end of line post fault current phasor. All possible combination of faults involving three-phases and ground, can be classified, differentiating the faulted phase(s) from the non-faulted phase(s). Different test cases by varying fault resistance, fault distance and inception angle is used to verify adoptability of suggested technique. In MATLAB/ SIMULINK, simulation studies are done using SimPowerSystems and Fuzzy Logic Toolbox.

Keywords: Transmission line, Fuzzy logic system (FLS), Fault inception angle (FIA), Fault detection (FD), Discrete Fourier transform (DFT), Fault classification (FC).

I. INTRODUCTION

The faults are unavoidable and can cause instability and unexpected failures in the transmission line. For protection of transmission line accurate detection and classification as quick as possible is must to achieve the stability again. An effective relaying system is able to respond the irregular condition, if identified, in the transmission line and isolate it from the rest healthy line of the system to prevent fault propagation into healthy part and safeguards the line from transient effects of the fault.

Artificial intelligence (AI) based systems such as artificial neural network (ANN), fuzzy logic, neuro-fuzzy etc. are the recent protection approaches. ANN-based fault location [1]-[4] and distance protection [5]-[7], fuzzy and fuzzy-neural-network [8]-[11] based operations are different fault classification techniques.

The ANN based approaches are precise to evaluate the fault nature, though, it require tedious training tactics to entire fault and operational settings such as fault resistance, fault inception angle, fault location, system pre-fault load, etc. On the other hand, the most important advantage of Fuzzy set is simple “If-Then” technique. Also, the fuzzy logic are simple and fast independent system, in comparison to ANN.

In [8], only LG (line to ground) and LLG (double line to ground) faults are classified, whereas in [1]-[7], [9] & [10] whether LG, LL, LLG or symmetrical fault i.e. nature of the fault is determined. In [11], all possible types of short circuit faults is evaluated with the use of only the magnitude and phase angle of three phase currents. Unluckily, the proposed fuzzy based logic in [11] delivers errors in high distances from relaying point, high system loading level and high fault resistance.

To avoid mentioned limitations an enhanced fuzzy logic-based method capable of high accurate fault classification of transmission line under variation of fault resistance, fault location, and fault inception angle is suggested using only amplitude of current signals from sending end side. Simulation of different fault cases is done to examine the performance of system.

II. SIMULATION OF POWER SYSTEM NETWORK

A 220 kV, 50Hz transmission line system is used to develop the suggested approach with the use of fuzzy logic. Single-line diagram of the system is shown in Fig. 1. Two sources each of 220 kV located at both ends along with three phase fault simulator is present in the transmission line. Simulink and Sim Power System toolbox of MATLAB is used for the study.

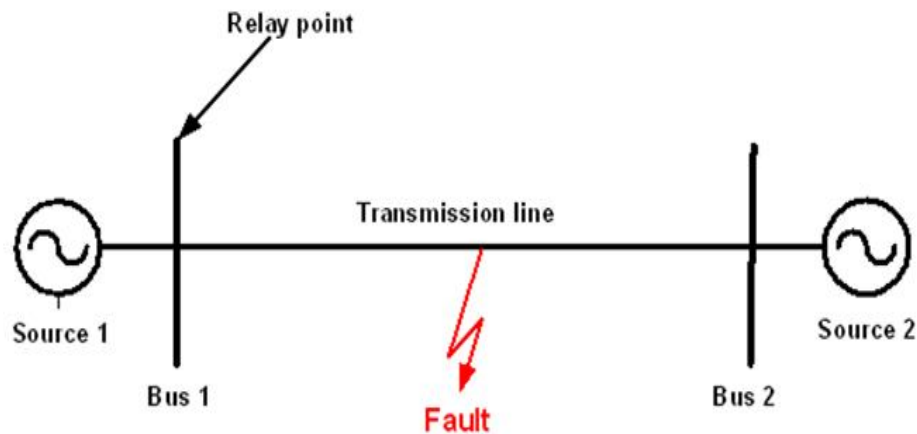


Fig.1 Single line diagram of simulated power system network

III. FAULT CLASSIFICATION SCHEME

By extensive simulation studies carried out on the power system model shown in Fig. 1 using MATLAB, fault classification technique is developed. Post-fault samples of three phase currents are considered where magnitudes of each fundamental current signals recorded at the relay location. With the use of Discrete Fourier Transform (DFT) magnitudes of current signals are calculated as characteristic features and given as input for FLS. The fault classification algorithm based on fundamental magnitudes of phase currents and angular differences among the sequence components of the fundamental fault current.

The characteristic features are calculated in terms of $\Delta 1$, $\Delta 2$, $\Delta 3$ and $\Delta 4$ from the fundamental current magnitudes of the phase currents and the characteristic features are calculated in terms of ang_A , ang_B , and ang_C which are angular difference among the sequence components of the fundamental fault currents. These characteristics features are calculated as described below.

A. Characteristics Features Calculations using Current Magnitudes

From three First of all, from the post-fault current samples the ratios $R1$, $R2$ and $R3$ are calculated as follows:

$$R1 = \max \{ \text{abs} (I_a) \} / \max \{ \text{abs} (I_b) \}$$

$$R2 = \max \{ \text{abs} (I_b) \} / \max \{ \text{abs} (I_c) \}$$

$$R3 = \max \{ \text{abs} (I_c) \} / \max \{ \text{abs} (I_a) \}$$

Where I_a , I_b , I_c are the post-fault samples of the three phase currents. Next, the normalized values of $R1$, $R2$ and $R3$ are found out as follows:

$$R1n = R1 / \max (R1, R2, R3)$$

$$R2n = R2 / \max (R1, R2, R3)$$

$$R3n = R3 / \max (R1, R2, R3)$$

Finally, the differences of these normalized values are found out as follows.

$$\Delta 1 = R1n - R2n$$

$$\Delta 2 = R2n - R3n$$

$$\Delta 3 = R3n - R1n$$

To indicate the presence of ground in the fault the ratio of zero sequence current and positive sequence current is calculated as:

$$\Delta 4 = \text{abs} (I_0) / \text{abs} (I_1)$$

When $\Delta 4$ exceeds the threshold value, it indicates that a fault involving ground has occurred otherwise a line-to-line fault not involving ground has occurred. The characteristic features of different types of fault are determined in of $\Delta 1$, $\Delta 2$, $\Delta 3$ and $\Delta 4$.

B. Characteristics Features Calculations using Sequence Currents

For an example, when a phase-a-to-ground bolted fault occurs in an unloaded system, the phasor diagram of sequence components of fault currents is shown in Fig. 2.

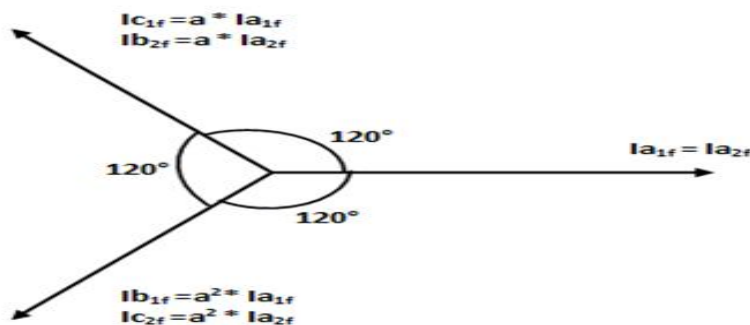


Fig. 2 Phasor diagram for a-g fault

In figure 2, the post fault currents relative to phase “a” are denoted as I_{a1f} for positive and I_{a2f} for negative sequence respectively. Similarly, the sequence components for phases “b” and “c” are denoted as I_{b1f} , I_{b2f} and I_{c1f} and I_{c2f} respectively. The symbol “a” is a complex operator whose value is

$$a = 1 \angle 120^\circ$$

From Fig. 2, the angles between the positive and negative sequence components of phase a, b, and c are given below.

$$\text{ang_A} = |\text{ang}(I_{a1f}) - \text{ang}(I_{a2f})| = 0^\circ$$

$$\text{ang_B} = |\text{ang}(I_{b1f}) - \text{ang}(I_{b2f})| = 120^\circ$$

$$\text{ang_C} = |\text{ang}(I_{c1f}) - \text{ang}(I_{c2f})| = 120^\circ$$

Similar these relationships can also be written for other type of asymmetrical faults (i.e., b-g, c-g, a-b, b-c, c-a, a-b-g, b-c-g, and c-a-g) and these relations are given in Table 1.

For symmetrical faults, the zero and negative sequence currents do not present in the system. Hence, the angles Ang_A , Ang_B and Ang_C are not defined for this case. Now it is to be noted that the relationships given in Table 1 are only valid for solid faults in an unloaded system. On considering present pre-fault power level, fault location, fault inception angle and fault resistance, values of Ang_A , Ang_B and Ang_C will get varied from their ideal values (as given in Table 1). A large number of fault studies is carried out under varying combinations of fault location, fault resistance and fault inception angle and the values have been computed for each of these faults. From these data, the mean values of each of these three quantities have been calculated for each specific type of fault and subsequently, these mean values have been rounded to their nearest whole number.

For an example, the mean value of the variable has been found to be 26.75, which has been rounded to its nearest whole number (i.e., 30). Similar exercises have been carried out for the other variables also. Now, for subsequent reference, these rounded, nearest whole numbers would be termed as “approximate mean value.” These mean values are given in Table 2.

TABLE I
FUNDAMENTAL RELATIONS FOR
VALUES OF

Type of Fault	Ang_A	Ang_B	Ang_C
a-g	0°	120°	120°
b-g	120°	0°	120°
c-g	120°	120°	0°
a-b-g	60°	60°	180°
b-c-g	180°	60°	60°
c-a-g	60°	180°	60°
a-b	60°	60°	180°
b-c	180°	60°	60°
c-a	60°	180°	60°
Symmetrical	-	-	-

TABLE II
APPROXIMATE MEAN
ASYMMETRICAL FAULTS
DIFFERENT QUANTITIES

Type of Fault	Ang_A	Ang_B	Ang_C
a-g	30°	150°	90°
b-g	90°	30°	150°
c-g	150°	90°	30°
a-b-g	30°	90°	150°
b-c-g	150°	30°	90°
c-a-g	90°	150°	30°
a-b	30°	90°	150°
b-c	150°	30°	90°
c-a	90°	150°	30°
Symmetrical	-	-	-

IV.DEVELOPMENT OF FUZZY LOGIC BASED FAULT CLASSIFIER

A Fuzzy logic system (FLS) uses a collection of fuzzy membership functions and rules, instead of Boolean logic, to reason about data. Basically, a Fuzzy knowledge based system comprises of three parts, namely, Fuzzification, inference rules and Defuzzification which are described in the following sections.

A. Fuzzification

FLS has input variables $\Delta 1$, $\Delta 2$, $\Delta 3$, $\Delta 4$, Ang_A, Ang_B and Ang_C. The output variables for FLS are Trip1, Trip2 which are expressed by u1, and u2 respectively. The linguistic input variables contain two fuzzy subsets: 1) high (H); 2) low (L). The linguistic output variables contain two fuzzy subsets: 1) Trip high (TH); 2) Trip low (TL). Fuzzy ratings for input and output linguistic terms are shown in Table 3, 4, 5 and 6 respectively. Triangular-shaped membership functions are used for input and output variables as shown in Fig.3. The membership functions are selected on a hit and trial basis with the aim of improving the classification accuracy.

Table III
fuzzy ratings for input
Linguistic terms $\Delta 1$, $\Delta 2$, $\Delta 3$

Linguistic terms	Fuzzy numbers
low	[-1 -0.5 0]
medium	[-0.1 0.1 0.3]
high	[0.12 0.55 1]

Table Iv
fuzzy ratings for input
linguistic terms $\Delta 4$

Linguistic terms	Fuzzy numbers
low	[0 .015 0.03]
high	[0.03 0.55 1]

TABLE V
FUZZY RATINGS FOR INPUT LINGUISTIC
FOR OUTPUT
TERMS Ang_A, Ang_B and Ang_C

Linguistic terms	Fuzzy numbers
Ang_A	[0 30 60]
Ang_B	[60 90 120]
Ang_C	[120 150 180]

TABLE VI
FUZZY RATINGS

LINGUISTIC TERMS	
Linguistic terms	Fuzzy numbers
AG	[4.5 5 5.5]
BG	[9.5 10 10.5]
CG	[14.5 15 15.5]
ABG	[19.5 20 20.5]
BCG	[24.5 25 25.5]
CAG	[29.5 30 30.5]
AB	[34.5 35 35.5]
BC	[39.5 40 40.5]
CA	[44.5 45 45.5]
ABC	[49.5 50 50.5]

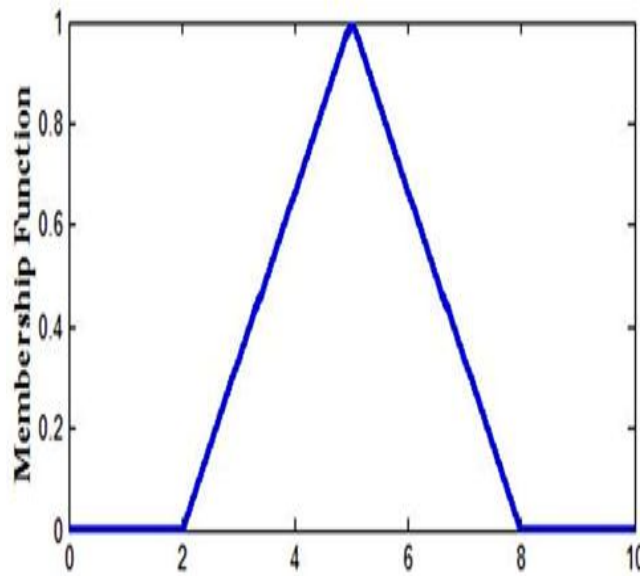


Fig. 3 Triangular membership functions for outputs of phase fault

B. Fuzzy Inference Rules

To ensure the change trends of output variables, based on a set of extensive simulation, the rules of fuzzy knowledge based systems are given below. The output membership function of each rule is calculated by the MAX-MIN method proposed in the relative.

- 1) If $\Delta 1$ is high & $\Delta 2$ is medium & $\Delta 3$ is low & $\Delta 4$ is high & Ang_A is $\text{aprx}30^\circ$ & Ang_B is $\text{aprx}150^\circ$ & Ang_C is $\text{aprx}90^\circ$ then fault type is “a-g”.
- 2) If $\Delta 1$ is low & $\Delta 2$ is high & $\Delta 3$ is medium & $\Delta 4$ is high & Ang_A is $\text{aprx}90^\circ$ & Ang_B is $\text{aprx}30^\circ$ & Ang_C is $\text{aprx}150^\circ$ then fault type is “b-g”.
- 3) If $\Delta 1$ is medium & $\Delta 2$ is low & $\Delta 3$ is high & $\Delta 4$ is high & Ang_A is $\text{aprx}150^\circ$ & Ang_B is $\text{aprx}90^\circ$ & Ang_C is $\text{aprx}30^\circ$ then fault type is “c-g”.
- 4) If $\Delta 1$ is low & $\Delta 2$ is high & $\Delta 3$ is low & $\Delta 4$ is high & Ang_A is $\text{aprx}30^\circ$ & Ang_B is $\text{aprx}90^\circ$ & Ang_C is $\text{aprx}150^\circ$ then fault type is “a-b-g”.
- 5) If $\Delta 1$ is low & $\Delta 2$ is low & $\Delta 3$ is high & $\Delta 4$ is high & Ang_A is $\text{aprx}150^\circ$ & Ang_B is $\text{aprx}30^\circ$ & Ang_C is $\text{aprx}90^\circ$ then fault type is “b-c-g”.
- 6) If $\Delta 1$ is high & $\Delta 2$ is low & $\Delta 3$ is low & $\Delta 4$ is high & Ang_A is $\text{aprx}90^\circ$ & Ang_B is $\text{aprx}150^\circ$ & Ang_C is $\text{aprx}30^\circ$ then fault type is “c-a-g”.
- 7) If $\Delta 1$ is low & $\Delta 2$ is high & $\Delta 3$ is low & $\Delta 4$ is low & Ang_A is $\text{aprx}30^\circ$ & Ang_B is $\text{aprx}90^\circ$ & Ang_C is $\text{aprx}150^\circ$ then fault type is “a-b”.
- 8) If $\Delta 1$ is low & $\Delta 2$ is low & $\Delta 3$ is high & $\Delta 4$ is low & Ang_A is $\text{aprx}150^\circ$ & Ang_B is $\text{aprx}30^\circ$ & Ang_C is $\text{aprx}90^\circ$ then fault type is “b-c”.
- 9) If $\Delta 1$ is high & $\Delta 2$ is low & $\Delta 3$ is low & $\Delta 4$ is low & Ang_A is $\text{aprx}90^\circ$ & Ang_B is $\text{aprx}150^\circ$ & Ang_C is $\text{aprx}30^\circ$ then fault type is “c-a”.
- 10) If $\Delta 1$ is medium & $\Delta 2$ is medium & $\Delta 3$ is low & $\Delta 4$ is low & Ang_A is none & Ang_B is none & Ang_C is none then fault type is “a-b-c”.
- 11) If $\Delta 1$ is medium & $\Delta 2$ is low & $\Delta 3$ is medium & $\Delta 4$ is low & Ang_A is none & Ang_B is none & Ang_C is none then fault type is “a-b-c”.
- 12) If $\Delta 1$ is low & $\Delta 2$ is medium & $\Delta 3$ is medium & $\Delta 4$ is low & Ang_A is none & Ang_B is none & Ang_C is none then fault type is “a-b-c”. A “Mamdani” type of Fuzzy Inference System (FIS) was utilized for taking the crisp output of the fault type. To implement the fuzzy inference system, the “min” and “max” operators were used for “and”, “implication” and “aggregation” methods, respectively. The “centroid” defuzzification method was used to defuzzify the output of the fuzzy inference system [15].

V. RESULTS OF FUZZY LOGIC BASED FAULT CLASSIFIER

Simulation of three phase transmission line model has been done at different fault location, fault resistance and fault inception angle for all phase to phase and phase to ground faults to verify the performance of the fuzzy logic based fault classifier. The simulation test result of all possible types of shunt faults (LG, LLG, LL and LLL) are given in Table 7, 8, 9 and 10.

TABLE VII

SIMULATION RESULT OF FUZZY LOGIC BASED

FAULT CLASSIFIER FOR LG FAULTS

Fault Type	Fault Conditions			Output Variables	
	R _f (ohm)	Φ _i (deg)	L _f (km)	Desired Output	Actual Output
A-G	1	30	1	5	4.95
	120	150	50		4.95
	200	270	75		4.95
	300	360	99.5		4.95
B-G	1	30	1	10	10.17
	120	150	50		10.04
	200	270	75		10.16
	300	360	99.5		10.18
C-G	1	30	1	15	15.13
	120	150	50		15.08
	200	270	75		15.13
	300	360	99.5		15.12

TABLE IX

SIMULATION RESULT OF FUZZY LOGIC BASED

LOGIC BASED

FAULT CLASSIFIER FOR LL FAULTS

FAULT CLASSIFIER FOR LLL FAULTS

Fault Type	Fault Conditions			Output Variables	
	R _f (ohm)	Φ _i (deg)	L _f (km)	Desired Output	Actual Output
AB	0.01	30	1	35	34.93
	0.01	150	50		34.92
	0.01	270	75		34.93
	0.01	360	99.5		34.92
BC	0.01	30	1	40	39.88
	0.01	150	50		39.88
	0.01	270	75		39.88
	0.01	360	99.5		39.88
AC	0.01	30	1	45	44.82
	0.01	150	50		44.82
	0.01	270	75		44.82
	0.01	360	99.5		44.83

TABLE VIII

SIMULATION RESULT OF FUZZY LOGIC

FAULT CLASSIFIER FOR LLG FAULTS

Fault Type	Fault Conditions			Output Variables	
	R _f (ohm)	Φ _i (deg)	L _f (km)	Desired Output	Actual Output
AB-G	1	30	1	20	20.07
	120	150	50		20.08
	200	270	75		20.07
	300	360	99.5		20.08
BC-G	1	30	1	25	25.02
	120	150	50		25.03
	200	270	75		25.02
	300	360	99.5		25.02
AC-G	1	30	1	30	29.88
	120	150	50		29.98
	200	270	75		29.98
	300	360	99.5		29.97

TABLE X

SIMULATION RESULT OF FUZZY

Fault Type	Fault Conditions			Output Variables	
	R _f (ohm)	Φ _i (deg)	L _f (km)	Desired Output	Actual Output
ABC	0.01	30	1	50	50.05
	0.01	150	50		50.05
	0.01	270	75		50.05
	0.01	360	99.5		50.05

From the test results given in Table 7-10, it is clear that the Fuzzy Logic based Fault Classifier is able to classify the fault accurately. Thus, even the extreme fault case of high impedance fault near the far end of the line is classified correctly by the developed Fuzzy Logic based Fault Classifier.

VI.CONCLUSIONS

For the digital protection of transmission line, proposed methodology can be implemented with only requirement of three phase post fault current samples at one end of line. The magnitudes of fundamental phase current and angular differences between sequence components of the fundamental fault current are considered for fault classification algorithm. Faults with ground and without involvement of ground is developed All the characteristics features participate in fuzzy logic system (FLS) and suitable rule base is designated for detection and classification of fault under varying fault resistance, fault inception angle and fault location. Obtained results confirm the adoptability of the proposed scheme hence applicable to enhance the present protection technology.

VII.ACKNOWLEDGMENT

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APPENDIX

Components	Parameters			
Three phase source	Voltage (kV)	220		
	Frequency(Hz)	50		
	Short circuit capacity (GVA)	1.25		
	X/R ratio	10		
Transmission line	Line length (km)	100		
	Line voltage (kV)	220		
	Sequence impedance(Ω /km)	Positive	0.0275 + j0.422	
		Zero	0.275 + j1.169	
	Sequence capacitance(nF/km)	Positive	9.483	
		Zero	6.711	

REFERENCES

- [1] R. N. Mahanty, and P. B. Dutta Gupta, "Application of RBF neural network to fault classification and location in transmission lines", IEE Proc.-Gener. Transm. Distrib., vol. 151, no. 2, pp. 201-212, March 2004.
- [2] D. Thukaram, H. P. Khincha and H. P. Vijaynarasimha, "Artificial neural network and support vector machine approach for locating faults in radial distribution system," IEEE Trans. on Power Delivery, vol. 20, no. 2, pp. 710-720, April 2005.
- [3] J. Gracia, A. J. Mazon, and I. Zamora, "Best ANN structures for fault location in single-and double-circuit transmission lines", IEEE Trans. on Power Delivery, vol. 20, no. 4, pp. 2389-2395, Oct. 2005.
- [4] M. TarafdarHagh, K. Razi, and G. Ahrabian "Fault classification and location of transmission lines using artificial neural network," The 8th International Power Engineering Conference – IPEC 2007, pp. 1541- 1546, 3-6 Dec. 2007.
- [5] P.K. Dash, A.K. Pradhan, and G. Panda, "Application of minimal radial basis function neural network to distance protection", IEEE Trans .on Power Deliv., vol. 16, no.1, pp. 68–74, 2001.
- [6] A.K. Pradhan, P.K. Dash, and G. Panda "A fast and accurate distance relaying scheme using an efficient radial basis function neural network," Electric Power Systems Research, pp. 1–8, 2001.
- [7] Sanaye-Pasand, M.; Khorashadi-Zadeh; "An extended ANN-based high speed accurate distance protection algorithm," Electrical Power and Energy Systems, pp. 387–395, 2006.
- [8] A. Ferrero, S. Sangiovanni, and E. Zaitelli, "A fuzzy set approach to fault type identification in digital relaying," IEEE Trans. on Power Delivery, vol. 10, pp. 169–175, Jan. 1995.
- [9] H.WangandW.W. L. Keerthipala, "Fuzzy neuro approach to fault classification for transmission line protection," IEEE Trans. on Power Delivery, vol. 13, pp. 1093–1104, Oct. 1998.
- [10] P. K. Dash, A. K. Pradhan, and G. Panda, "A Novel Fuzzy Neural Network Based Distance Relaying Scheme," IEEE Trans. on Power Delivery, vol. 15, no. 3, July 2000.
- [11] Biswarup Das, and J. Vittal Reddy, "Fuzzy-logic-based fault classification scheme for digital distance protection," IEEE Trans. On Power Delivery, vol. 20, no. 2, pp. 609-616, April 2005.
- [12] R.N.Mahanty and P.B.Gupta,2007,"A fuzzy logic based fault classification approach using current samples only",Electric Power Systems Research 77 ,pp 501–507.
- [13] PSCAD/EMTDC Version 4.01, Manitoba HVDC Research Center, Winnipeg, Manitoba, Canada.
- [14] MatLab, Natick, MA: The MathWorks.
- [15] Hung T. Nguyen, MichioSugeno, Fuzzy Systems: Modeling andControl, Kluwer Academic Publisher, Massachusetts, 1998.



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