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Classification of Faults in Power Transmission Lines using Fuzzy-Logic Technique

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Abstract

Transmission lines safeguard against exposed fault is the most critical task in the protection of power system. The purpose of a protective relaying is to identify the abnormal signals representing faults on a power transmission system. So fault classification is necessary for reliable and high speed protective relaying. This paper uses fuzzy logic technique for fault classification and this study describes a new approach to distinctly identify and classify ground and phase faults by using two separate fuzzy classifiers. Samples of post fault currents from all three phases at one end of the transmission system are being used to classify the nature of the faults. To demonstrate the effectiveness of this method, simulations considering various operating conditions have been performed on MATLAB. The simulation studies of the proposed technique indicate that the accuracy in fault classification increases because of two fuzzy classifiers is used for fault analysis.

Keywords: Fault, Fault Classification, Fuzzy Logic, Fuzzy Inference System, Overhead Lines, Transmission Line Protection

1. Introduction

Power grids around the globe are undergoing massive transformation towards smart power grids with the help of rapidly developing monitoring and control methodology. Among these detecting the fault and the phase which underwent the fault is of great importance. Classification of fault has the area of interest for numerous researchers and as an outcome several fault classification methods have been implemented over the time. Some of the prominent methods are: Neural network based technique, wavelet transforms based technique, fuzzy and fuzzy-network based technique, etc.

Thomas Dalstein and Bemd Kulicke have proposed a method using digital signal processing implementation and neural network architecture concept for fault classification[1]. Alessandro Ferrero et al., proposed an approach to find the fault type using fuzzy set approach[2]. Huisheng Wang et al., presented a novel method to real-time classification of faults in transmission lines with the help of neuro-fuzzy methods[3]. A travelling waves and fuzzy logic technique has been presented by Parmod Kumar et al., in[4]. A novel method to real-time classification of faults in transmission lines using fuzzy-logic developed[5,6]. A new approach using Fuzzy Neural Network (FNN) to distance relaying was presented[8]. Kaveh Razi et al., presented an approach to classify faults using fuzzy logic approach and full cycle discrete Fourier transform[9]. The wavelet technique uses the method of oscillography[10]. The information of faults and power quality disturbances are recorded in the form of oscillogarphic data. This kind of computation is quiet complex and uses a lot of processing power. A fault location technique has been developed using wavelet-fuzzy[11] and wavelet and neuro-fuzzy based methods[13]. Wavelet coefficient energies of the fault-induced transients were used for fault analysis[14]. Carlo Cecati et al.,

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used fuzzy-logic method to increase the accuracy in fault classification[15]. The advantage of this approach is, it can separate the faulty and non-faulty phases[15]. S. R. Samantaray proposed a novel method to analyze the faults in transmission system based on fuzzy rule technique, and a comparison was also made between wavelet transform and s-transform[16]. R. N. Mahanty et al., developed an approach for fault analysis using current samples with the help of fuzzy logic[17]. The neural network technique needs rigorous training of the nodes, wavelet transform, neuro-fuzzy techniques are computationally complex. Fuzzy logic approach compared to these methods less complex and user friendly. The importance of fuzzy logic technique in power systems increases due to its robust nature. The fuzzy controllers used in various applications like power system stabilizer for damping[7], inverted pendulum-type mobile robot[12] and especially in compensation of voltage sag/swell problems[18].

The proposed technique can improve accuracy of the classification of faults by using two different fuzzy classifiers. This paper describes the use of fuzzy logic approach to distinctly identify the nature of fault. Samples of three phase post fault current are being considered for the classification of fault. Simulation has been performed considering a wide variety of conditions to satisfy the validity of the proposed method. The generated fault data from the simulation has been used to feed the "Fuzzy logic toolbox" of MATLAB.

2. Fault Detection Technique

The power system model single line diagram which has been considered for the simulation shown in Figure 1. A 200 km transmission line length, 400 kv source voltage and load angle of 20^0 for 3 phase system considered to simulate the proposed technique.

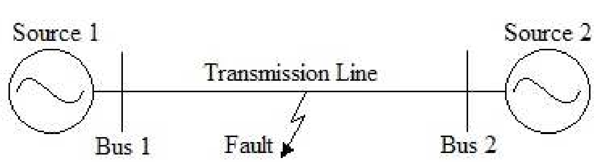

Figure 1. Power system model.

The fault can be detected by using fault index (Ø), Ø = max(Ia + Ib + Ic);

Where I_a, I_b, I_c are phase currents. If the value of fault index (Ø) greater than 100, it indicates ground faults and if Ø value is less than 1 means it indicates phase faults. By using this relation, it is easy to find weather the occurred fault is ground fault or phase fault. Table 1 and Table 2 shows different values of Ø for different fault resistances in case of both ground faults and phase faults.

Table 1. Fault index (Ø) values in case of ground faults

Nature of Fault	For R_f = 25 Ω	For R_f = 50 Ω	For R_f = 75 Ω	For R_f = 100 Ω
	Ø (Amps)	Ø (Amps)	Ø (Amps)	Ø (Amps)
AG	1.3110e+03	840.5277	615.5372	480.0975
BG	1.3581e+03	856.0597	607.1148	464.9773
CG	1.3074e+03	851.7007	618.7031	484.1717
ABG	1.0403e+03	724.5282	562.7082	452.5997
BCG	1.0462e+03	730.7011	562.3221	449.3654
CAG	1.0783e+03	770.8454	571.1075	445.6502

Table 2. Fault index (Ø) values in case of phase faults

Nature of Fault	For R_f = 25 Ω	For R_f = 50 Ω	For R_f = 75 Ω	For R_f = 100 Ω
	Ø (Amps)	Ø (Amps)	Ø (Amps)	Ø (Amps)
AB	0.0303	0.0303	0.0303	0.0303
BC	0.0275	0.0275	0.0275	0.0275
CA	0.0292	0.0292	0.0292	0.0292
ABC	6.8103e-08	1.4786e-07	7.0414e-08	7.3267e-08

3. Fault Classification

The general process performed in a fuzzy logic approach is shown in Figure 2.

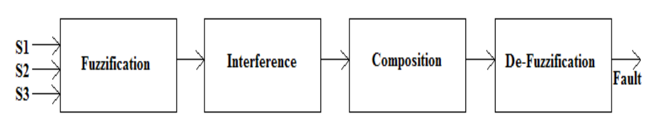

Figure 2. Fuzzy system.

The S_1, S_2 and S_3 in Figure 2 are inputs to the fuzzy system, the calculation[17] of these input variables using currents at one end of the system are given below.

The ratios P_1, P_2 and P_3 are calculated using post-fault currents, as follows:

$$P1 = \frac{\max\{abs(Ia)\}}{\max\{abs(Ib)\}},\ P2 = \frac{\max\{abs(Ib)\}}{\max\{abs(Ic)\}}$$

$$P3 = \frac{\max\{abs(Ic)\}}{\max\{abs(Ia)\}}$$

Next, the values of S_1, S_2 and S_3 are found out as follows:

$$P1(n) = \frac{P1}{\max(P1, P2, P3)},\ P2(n) = \frac{P2}{\max(P1, P2, P3)}$$

$$P3(n) = \frac{P3}{\max(P1, P2, P3)}$$

Lastly, the differences of these $P_1(n)$, $P_2(n)$ and $P_3(n)$ are calculated as follows:

$$S_1 = P_1(n) - P_2(n),\ S_2 = P_2(n) - P_3(n),\ S_3 = P_3(n) - P_1(n)$$

4. Implementation of Fuzzy Logic Approach

The Values of S_1, S_2 and S_3 are three inputs to the fuzzy classifier, used to classify nature of the fault; the general structure of Fuzzy Inference System (FIS) used in this technique is shown in Figure 3. The proposed technique using two classifiers one is for ground faults (Fuzzy classifier-I) and second one is for phase faults (Fuzzy classifier-II).

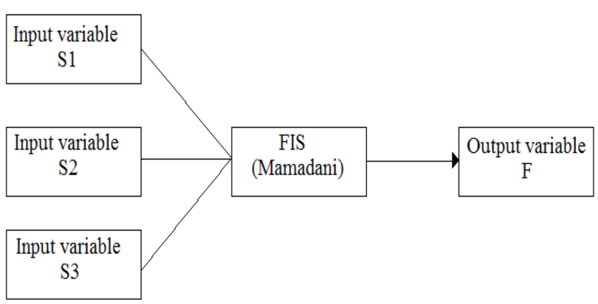

Figure 3. Fuzzy inference system.

4.1 Fuzzy Classifier-I for Ground Faults

For each input 3 triangular membership functions are chosen designated as $Small_g$, $Medium_g$ and $Large_g$. The membership function ranges for inputs are, value between -1.0 and -0.005 for $Small_g$, value between 0.02 and 0.3 for $Medium_g$, and value between 0.2 and 1.0 for $Large_g$. Figure 4 shows the membership functions of the inputs and Figure 5 shows the triangular membership functions of the outputs designated as AG, BG, CG, ABG, BCG, and CAG. Table 3 shows the output variables for ground faults.

Rules to find nature of ground faults using values of S_1, S_2 and S_3.

- If (S_1 is $Large_g$) and (S_2 is $Medium_g$) and (S_3 is $Small_g$) then (trip output is AG)
- If (S_1 is $Small_g$) and (S_2 is $Large_g$) and (S_3 is $Medium_g$) then (trip output is BG)

Table 3. Output variables for fuzzy classifier – I

Fault Type	Output (F)
AG	5
BG	10
CG	15
ABG	20
BCG	25
CAG	30

- If (S_1 is $Medium_g$) and (S_2 is $Small_g$) and (S_3 is $Large_g$) then (trip output is CG)
- If (S_1 is $Small_g$) and (S_2 is $Large_g$) and (S_3 is $Small_g$) then (trip output is ABG)
- If (S_1 is $Small_g$) and (S_2 is $Small_g$) and (S_3 is $Large_g$) then (trip output is BCG)
- If (S_1 is $Large_g$) and (S_2 is $Small_g$) and (S_3 is $Small_g$) then (trip output is CAG)

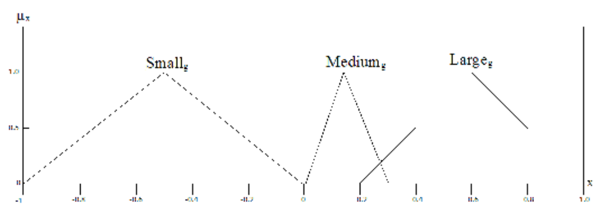

Figure 4. Triangular membership functions for inputs.

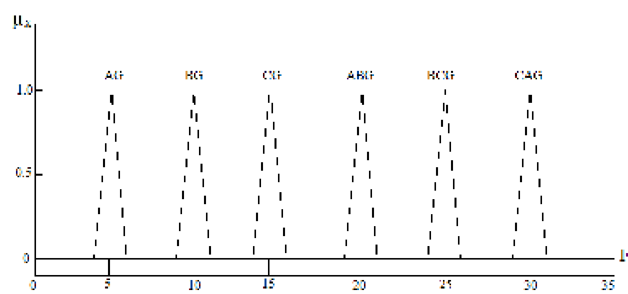

Figure 5. Triangular membership functions for outputs.

4.2 Fuzzy Classifier-II for Phase Faults

For each input 3 triangular membership functions are chosen designated as $Small_{ph}$, $Medium_{ph}$ and $Large_{ph}$. The membership function ranges for inputs are value between -1.0 and -0.005 for $Small_{ph}$, value between 0.01 and 0.6 for $Medium_{ph}$, and value between 0.5 and 1.0 for $Large_{ph}$. Figure 6 shows the membership functions of the inputs and Figure 7 shows the triangular membership functions of the outputs designated as Ab, BC, CA and ABC. The Table 4 shows the output variables for phase faults.

Table 4. Output variables for fuzzy classifier – II

Fault Type	Output (F)
AB	35
BC	40
CA	45
ABC	50

Rules to find nature of phase faults.

- If (S_1 is $Small_{ph}$) and (S_2 is $Large_{ph}$) and (S_3 is $Small_{ph}$) then (trip output is AB)
- If (S_1 is $Small_{ph}$) and (S_2 is $Small_{ph}$) and (S_3 is $Large_{ph}$) then (trip output is BC)
- If (S_1 is $Large_{ph}$) and (S_2 is $Small_{ph}$) and (S_3 is $Small_{ph}$) then (trip output is CA)
- If (S_1 is $Medium_{ph}$) and (S_2 is $Medium_{ph}$) and (S_3 is $Small_{ph}$) then (trip output is ABC)
- If (S_1 is $Small_{ph}$) and (S_2 is $Medium_{ph}$) and (S_3 is $Medium_{ph}$) then (trip output is ABC)
- If (S_1 is $Medium_{ph}$) and (S_2 is $Small_{ph}$) and (S_3 is $Medium_{ph}$) then (trip output is ABC)
- If (S_1 is $Small_{ph}$) and (S_2 is $Small_{ph}$) and (S_3 is $Medium_{ph}$) then (trip output is ABC)
- If (S_1 is $Medium_{ph}$) and (S_2 is $Small_{ph}$) and (S_3 is $Small_{ph}$) then (trip output is ABC)
- If (S_1 is $Small_{ph}$) and (S_2 is $Medium_{ph}$) and (S_3 is $Small_{ph}$) then (trip output is ABC)

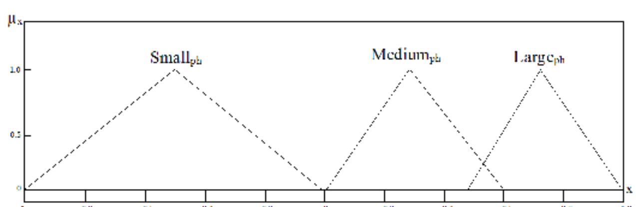

Figure 6. Triangular membership functions for inputs.

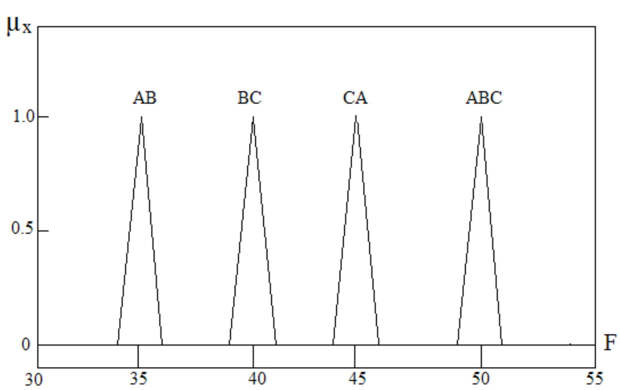

Figure 7. Triangular membership functions for outputs.

Table 5. Outputs for fuzzy classifier - I for ground faults

Nature of Fault	For $R_f = 25\ \Omega$				For $R_f = 50\ \Omega$				For $R_f = 75\ \Omega$				For $R_f = 100\ \Omega$			
	S_1	S_2	S_3	Fuzzy Output	S_1	S_2	S_3	Fuzzy Output	S_1	S_2	S_3	Fuzzy Output	S_1	S_2	S_3	Fuzzy Output
AG	0.9633	0.0324	-0.9957	5.1000	0.9400	0.0497	-0.9896	5.1000	0.9167	0.0647	-0.9814	5.1000	0.8927	0.0782	-0.9709	5.1000
BG	-0.9941	0.9684	0.0257	9.9000	-0.9871	0.9540	0.0331	9.9000	-0.9773	0.9297	0.0477	9.9000	-0.9670	0.8981	0.0689	9.9000
CG	0.0336	-0.9960	0.9625	15	0.0587	-0.9910	0.9323	15.0000	0.0840	-0.9834	0.8994	15	0.1096	-0.9736	0.8641	15
ABG	-0.9615	0.9978	-0.0364	20.1000	-0.9293	0.9930	-0.0637	20.1000	-0.8987	0.9862	-0.0875	20.1000	-0.8741	0.9779	-0.1038	20.1000
BCG	-0.0375	-0.9599	0.9974	24.9000	-0.0580	-0.9347	0.9927	24.9000	-0.0842	-0.9013	0.9855	24.9000	-0.1048	-0.8725	0.9773	24.9000
CAG	0.9972	-0.0411	-0.9561	30	0.9918	-0.0654	-0.9264	30	0.9837	-0.0901	-0.8937	30	0.9734	-0.1131	-0.8603	30

Table 6. Outputs for fuzzy classifier - II for phase faults

Nature of Fault	For R_f = 25 Ω				For R_f = 50 Ω				For R_f = 75 Ω				For R_f = 100 Ω			
	S_1	S_2	S_3	Fuzzy Output	S_1	S_2	S_3	Fuzzy Output	S_1	S_2	S_3	Fuzzy Output	S_1	S_2	S_3	Fuzzy Output
AB	-0.9516	0.9979	-0.0463	35.1000	-0.9075	0.9933	-0.0858	35.1000	-0.8681	0.9875	-0.1195	35.1000	-0.8254	0.9800	-0.1546	35.1000
BC	-0.0476	-0.9502	0.9978	39.9000	-0.0830	-0.9108	0.9937	39.9000	-0.1197	-0.8678	0.9875	39.9000	-0.1595	-0.8194	0.9789	39.9000
CA	0.9978	-0.0480	-0.9498	45	0.9930	-0.0880	-0.9049	45	0.9851	-0.1317	-0.8533	45	0.9742	-0.1785	-0.7957	45
ABC	0.0127	-0.0551	0.0424	50.1000	-0.0117	-0.0191	0.0308	50.1000	-0.0258	-0.0207	0.0464	50.1000	-0.0383	-0.0235	0.0619	50.1000

5. Results

The outputs for fuzzy classifier –I (ground faults) and fuzzy classifier – II (phase faults) are tabulated (Table 5 and 6).

6. Conclusion

A fuzzy logic based technique has been presented for the identification and classification of faults. The proposed technique requires considering the post fault currents of all three phases at one end of the transmission system. Based on the values of fault index (Ø), the presented technique detects the ground faults and phase faults. In this presented method, separate rules have been framed for both ground and phase faults. This respective input fed to the fuzzy classifier systems to classify nature of the fault. Simulation has been performed by considering various conditions to satisfy the efficiency of the presented technique. Simulation was carried out on a 400kV, 3 phase and 200km line to support the results of the proposed technique. The simulation results have led to conclude that the technique is quiet robust.

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