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Fuzzy Logic-Based Fault Classification for Transmission Line Analysis

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Abstract - *Transmission lines forms the backbone of the transmission and distribution networks, which powers the nation. No modern society can imagine its existence without power supplies, which runs everything ranging from consumer electronics to bullet trains. Electrical power systems suffer from unexpected failures due to various random causes. Unpredicted faults that occur in power systems are required to prevent from propagation to other area in the protective system. The functions of the protective systems are to detect, then classify and finally determine the location of the faulty line of voltage and/or current line magnitudes. Then at last, for isolation of the faulty line the protective relay have to send a signal to the circuit breaker. The ability to learn, generalize and parallel processing, fuzzy logic is powerful application to classify different type of fault in power system. This research paper focuses on classifying faults on electric power transmission lines. Fault classification have been achieved by using fuzzy logic and study on their result is done. The proposed technique is able to classify all the possible faults including single-phase to ground, two-phases, two-phases to ground and three-phase faults in transmission line.*

Key Words: fuzzy logic, transmission line, power, lightning etc

1. INTRODUCTION

The generation, transmission, and distribution of electric energy comprise an electric power system. Overhead transmission lines are the most cost-effective method of transporting electrical energy from sources of supply to load centres, resulting in electricity use and consumption. The rapid expansion of electric power networks in recent decades has resulted in a significant increase in the number of lines in operation and their total length. These lines are vulnerable to short circuits, overloads, tree branches, malfunctioning equipment, lightning, and human mistake. Most electrical problems exhibit as mechanical damage, which should be remedied before resuming service on the line. Any defect, if not recognised and isolated quickly, will evolve into a system-wide disturbing impact, producing blackouts and even power outages [1, 2].

When a fault occurs on a power system, economic losses can be reduced and line service can be maintained if the fault location is determined correctly, specifically while generation, transmission, and distribution occur over a longer distance, thereby improving the safety and quality of the power supply. If the detection, classification, and location of a problem on a line can be precisely determined, electric utility services can be maintained. These suitability variables and deductions make fault analyzers and their algorithms a crucial instrument in maintaining smart grid competency. Faults create short- to long-term power disruptions for clients and can result in significant losses, particularly for the manufacturing business [3].

Faster detection, categorization, and placement of these problems is critical for maintaining dependable power system operation. Deregulation of the power market, as well as financial and environmental constraints, have driven companies to run transmission lines to their most extreme limits of confinement. The smooth operation of electric power transmission lines is critical for conveying minimally interfered with control supply to purchasers, who have become progressively sensitive to control outages with the advancement of overall innovation. This necessitates the proper operation of electricity equipment as well as client pleasure. Engineers are thus compelled to develop transmission networks that construct power system protection algorithms to identify, categorise, and find defects that compromise system security. There are probable quick feasible repair and preservation approaches that specifically immediately increase power accessibility to consumers, which, in turn, improves the overall effectiveness of power systems. These availability, efficiency, and high-quality criteria are becoming increasingly important as a result of new marketing practises resulting from the deregulation and liberalisation of power and electrical markets. Saving time and effort, improving power accessibility, and keeping a strategic distance from future blunders can all be interpreted as a cost decrease or a benefit expansion [4].

As a result, there is a need to increase the accuracy of existing fault analysis methodologies. The increased size and complexity of power systems has necessitated the need for rapid and dependable relays to protect critical hardware and preserve system stability. Traditional shielding relays might be static or electromagnetic in nature. Electromagnetic relays have a number of drawbacks, including a long operating duration, an excessive load on instrument transformers, contact difficulties, and so on. Solid-state relays first appeared in the late 1950s. These were built with discrete electronic components such as operational amplifiers, transistors, and diodes. Static relays have been more popular in recent years because to their inherent advantages of minimal maintenance, low load, fast speed, and compactness. Although employed successfully, static relays have a number of drawbacks, including inadaptability, inflexibility to dynamical system circumstances, and complexity [5].

2. FUZZY LOGIC

FL excels in dealing with uncertainty, ambiguity, and imprecision. This is especially beneficial when a problem can be stated verbally (using words) or when there is data and one is seeking for links or patterns within that data, like with neural networks. It is a method of dealing with uncertainty that mixes real numbers [0...1] and logic operations.

FL is based on the ideas of fuzzy set theory and fuzzy set membership often found in natural (e.g., spoken) language. FL uses imprecision to provide robust solutions to problems. FL relies on the concept of a fuzzy set. The notation for fuzzy sets: for the member x, of a discrete set with membership μ, is μ/x. In other words, x is a member of the set to degree μ. Discrete sets are defined as:

$$A = \mu_1 / x_1 + \mu_2 / x_2 + \mu_3 / x_3 \ldots\ldots\ldots \mu_n / x_n \qquad (1)$$

FL systems are universal function approximates. In general, the goal of the FL system is to yield a set of outputs for given inputs in a nonlinear system without using any mathematical model. Fuzzy model is a collection of IF – THEN rules with vague predicates that use a fuzzy reasoning such as Sugeno and Mamdani models. Sugeno type systems can be used to model any inference system in which the output membership functions are either linear or constant whereas Mamdani type produces either linear or nonlinear output. FL controller contains four main parts, two of which perform transformations. The four parts are

- Fuzzifier (transformation 1)
- Knowledge base
- Inference engine (fuzzy reasoning, decision-making logic)
- Defuzzifier (transformation 2)

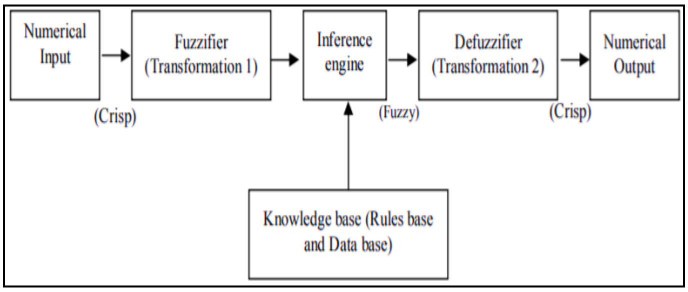

Figure -1: Schematic of FL system

3. Fault classification using Fuzzy System

The single line diagram of power system model is shown in fig 2

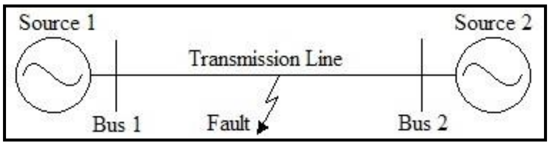

Figure -2. Power system model.

Table -1: Simulated Power System Parameters

Source Data at Both Sending and Receiving Ends	
Positive-sequence impedance (Ω)	1.31 + j 15.0
Zero-sequence impedance (Ω)	2.33 + j 26.6
Frequency (Hz)	50

Transmission Line Data	
Length (km)	300
Voltage (kV)	400
Positive-sequence impedance (Ω)	8.25 + j 94.5
Positive-sequence capacitance (nF/km)	13
Zero-sequence capacitance (nF/km)	8.5

The general process performed in a fuzzy logic approach is shown in Figure 3.

The S1, S2 and S3 in Figure 3 are inputs to the fuzzy system, the calculation of these input variables using currents at one end of the system are given below. The ratios P1, P2 and P3 are calculated using post-fault currents, as follows:

P1 max{abs(Ia)} / max{abs(Ib)} (2)
P2 = max{abs(Ib)}/max{abs(Ic)} (3)

P3 max{abs(Ic)}/max{abs(Ia)} (4)

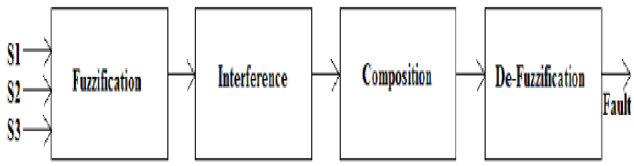

Figure -3: Fuzzy system

Next, the values of S1, S2 and S3 are found out as follows:

$$P_1(n) = \frac{P_1}{\max(P_1, P_2, P_3)} \quad (5)$$

$$P_2(n) = \frac{P_2}{\max(P_1, P_2, P_3)} \quad (6)$$

$$P_3(n) = \frac{P_3}{\max(P_1, P_2, P_3)} \quad (7)$$

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 S1, S2 and S3 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 4. The proposed technique using two classifiers one is for ground faults (Fuzzy classifier-I) and second one is for phase faults (Fuzzy classifier-II).

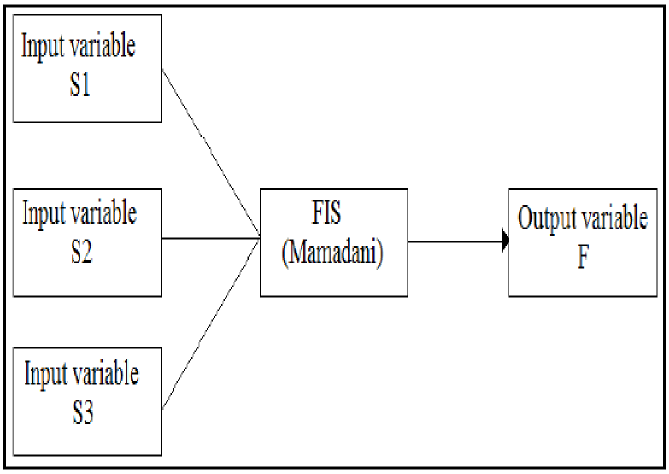

Figure -4: Fuzzy inference system

Fuzzy Classifier-I for Ground Faults

For each input 3 triangular membership functions are chosen designated as Smallg, Mediumg and Largeg. The membership function ranges for inputs are, value between -1 and -0.1 for Smallg, value between -0.1 and 0.2 for Mediumg, and value between 0.2 and 1.0 for Largeg.

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 2 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 (S1 is smallg) and (S2 is largeg) and (S3 is mediumg) then (F is AG).
- If (S1 is smallg) and (S2 is smallg) and (S3 is largeg) then (F is BG).
- If (S1 is mediumg) and (S2 is smallg) and (S3 is largeg) then (F is CG).
- If (S1 is Smallg) and (S2 is Largeg) and (S3 is Smallg) then (trip output is ABG).
- If (S1 is Smallg) and (S2 is Smallg) and (S3 is Largeg) then (trip output is BCG).
- If (S1 is Largeg) and (S2 is Smallg) and (S3 is Smallg) then (trip output is CAG).

Table -2: Output variables for fuzzy classifier – I

Nature of fault	Fuzzy output
AB	35
BC	40
CA	45
ABC	50

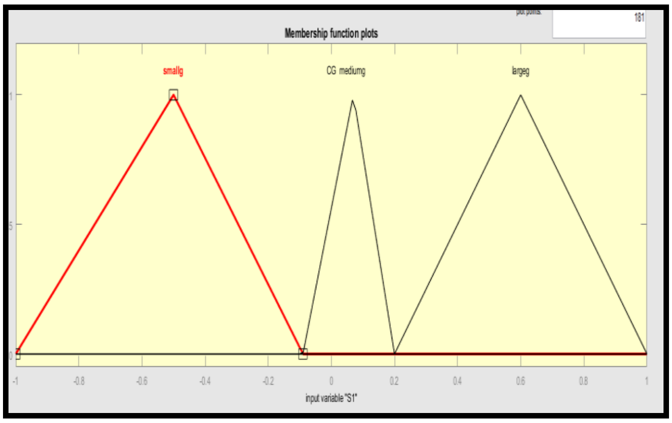

Figure -5: Triangular membership functions for inputs

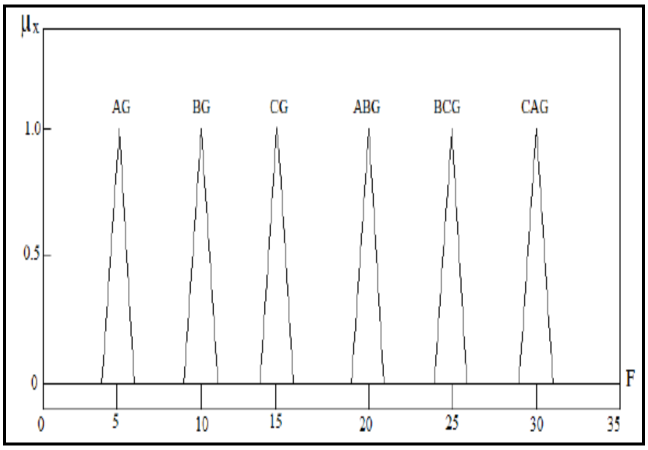

Figure -6: Triangular membership functions for outputs

Fuzzy Classifier-II for Phase Faults

For each input 3 triangular membership, functions are chosen designated as Smallph, Mediumph and Largeph. The membership function ranges for inputs are value between -1.0 and -0.005 for Smallph, value between 0.01 and 0.6 for Mediumph, and value between 0.5 and 1.0 for Largeph. Figure 7 shows the membership functions of the inputs and Figure 8 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 -3: Output variables for fuzzy classifier – II

Nature of fault	Fuzzy output
AB	35
BC	40
CA	45
ABC	50

Rules to find nature of phase faults.

- If (S1 is Smallph) and (S2 is Largeph) and (S3 is Smallph) then (trip output is AB)
- If (S1 is Smallph) and (S2 is Smallph) and (S3 is Largeph) then (trip output is BC)
- If (S1 is Largeph) and (S2 is Smallph) and (S3 is Smallph) then (trip output is CA)
- If (S1 is Mediumph) and (S2 is Mediumph) and (S3 is Smallph) then (trip output is ABC)
- If (S1 is Smallph) and (S2 is Mediumph) and (S3 is Mediumph) then (trip output is ABC)
- If (S1 is Mediumph) and (S2 is Smallph) and (S3 is Mediumph) then (trip output is ABC)
- If (S1 is Smallph) and (S2 is Smallph) and (S3 is Mediumph) then (trip output is ABC)
- If (S1 is Mediumph) and (S2 is Smallph) and (S3 is Smallph) then (trip output is ABC)
- If (S1 is Smallph) and (S2 is Mediumph) and (S3 is Smallph) then (trip output is ABC)

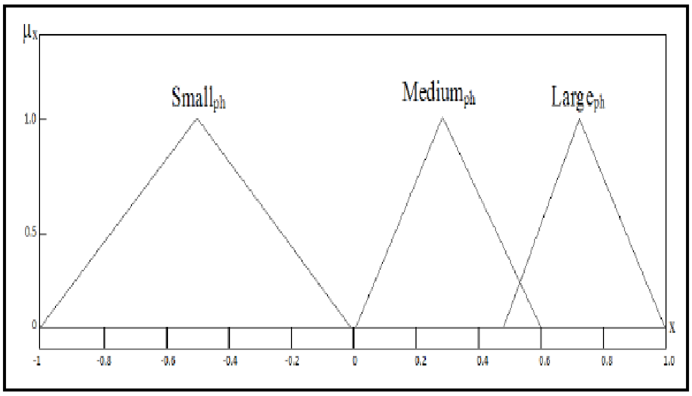

Figure -7: Triangular membership functions for input

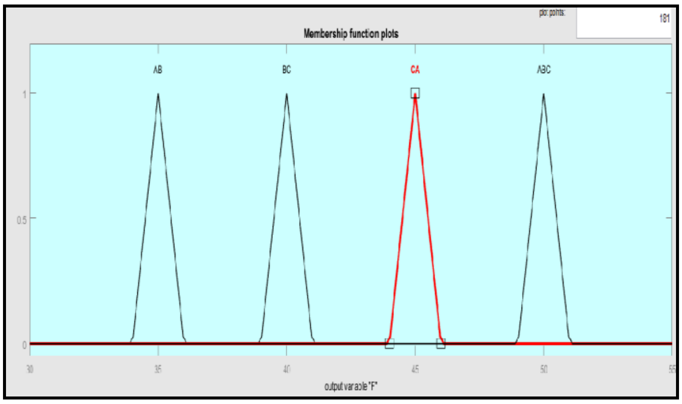

Figure -8: Fuzzy Membership function of faults

5. SIMULATION RESULTS

Output Fault values for fuzzy Classifier is shown in figure and tables.

Table -4: Output Fault values for fuzzy Classifier I

For Rf =25Ω				
Nature of fault	**S1**	**S2**	**S3**	**Fuzzy output**
AG	-0.2021	0.2394	-0.0373	5
BG	-0.3277	-0.4224	0.7501	10
CG	0.0120	-0.8428	0.8307	15
ABG	-0.7752	0.8560	-0.0808	19.9
BCG	-0.0838	0.8692	0.9531	25
CAG	0.8929	-0.4394	-0.4534	30

Table -5: Output Fault values for fuzzy Classifier II

For Rf =25Ω				
Nature of fault	**S1**	**S2**	**S3**	**Fuzzy output**
AB	-0.7926	0.8564	-0.0639	35
BC	-0.0909	-0.8832	0.9740	40
CA	0.9571	-0.3060	-0.6511	45
ABC	0.1852	-0.4915	0.3064	50

Table -6: Output Fault values for fuzzy Classifier I

For Rf =50Ω				
Nature of fault	**S1**	**S2**	**S3**	**Fuzzy output**
AG	-0.2008	0.2321	-0.0313	5
BG	-0.3270	-0.4244	0.7515	10
CG	0.0122	-0.8421	0.8298	15
ABG	-0.7735	0.8535	-0.0800	19.9
BCG	-0.0838	-0.8689	0.9528	25
CAG	0.8913	-0.4427	-0.4485	30

Table -7: Output Fault values for fuzzy Classifier II

For Rf =50Ω				
Nature of fault	**S1**	**S2**	**S3**	**Fuzzy output**
AB	-0.7910	0.8539	-0.0629	35
BC	-0.0913	-0.8822	0.9736	40
CA	0.9580	-0.3031	-0.6548	45
ABC	0.18347	-0.4905	0.3071	50

Table -8: Output Fault values for fuzzy Classifier I

For Rf =75Ω				
Nature of fault	**S1**	**S2**	**S3**	**Fuzzy output**
AG	-0.1995	0.2248	-0.0253	5
BG	-0.3264	-0.4264	0.7528	10
CG	0.0124	-0.8414	0.8290	15
ABG	-0.7718	0.8509	-0.0791	19.9
BCG	-0.0838	-0.8685	0.9524	25
CAG	0.8896	-0.4460	-0.4436	30

Table -9: Output Fault values for fuzzy Classifier II

For Rf =75Ω				
Nature of fault	**S1**	**S2**	**S3**	**Fuzzy output**
AB	-0.7895	0.8513	-0.0618	35
BC	-0.0919	-0.881	0.97315	40
CA	0.9571	-0.306	-0.6511	45
ABC	0.1817	-0.489	0.3078	50

Table -10: Output Fault values for fuzzy Classifier I

For Rf =100Ω				
Nature of fault	**S1**	**S2**	**S3**	**Fuzzy output**
AG	-0.1982	0.2175	-0.0192	5
BG	-0.3258	-0.4283	0.7542	10
CG	0.0126	-0.8407	0.8281	15
ABG	-0.7701	0.8483	-0.0782	19.9
BCG	-0.0839	-0.8681	0.9520	25
CAG	0.8879	-0.4492	-0.4386	30

Table -11: Output Fault values for fuzzy Classifier I

For Rf =100Ω				
Nature of fault	**S1**	**S2**	**S3**	**Fuzzy output**
AB	-0.7879	0.8487	-0.0608	35
BC	-0.0924	-0.8803	0.9727	40
CA	0.9563	-0.3089	-0.6473	45
ABC	0.1801	-0.4887	0.3085	50

Table -12: Output Fault values for fuzzy Classifier I

For Rf =150Ω				
Nature of fault	**S1**	**S2**	**S3**	**Fuzzy output**
AG	-0.1957	0.2028	-0.0070	5
BG	-0.3245	-0.4322	0.7568	10
CG	0.0130	-0.8394	0.8264	15
ABG	-0.7667	0.8431	-0.0763	20
BCG	-0.0840	-0.8673	0.9513	25
CAG	0.8845	-0.4557	-0.4288	30

Table -13: Output Fault values for fuzzy Classifier II

	For Rf =150Ω			
Nature of fault	**S1**	**S2**	**S3**	**Fuzzy output**
AB	-0.7849	0.8436	-0.0586	35
BC	-0.0934	-0.8784	0.9718	40
CA	0.9546	-0.3148	-0.6398	45
ABC	0.1767	-0.4868	0.3100	50
AB	-0.7849	0.8436	-0.0586	35
BC	-0.0934	-0.8784	0.9718	40

Table -14: Output Fault values for fuzzy Classifier I

	For Rf =200Ω			
Nature of fault	**S1**	**S2**	**S3**	**Fuzzy output**
AG	-0.1933	0.1880	0.0053	10
BG	-0.3233	-0.4361	0.7594	10
CG	0.0133	-0.8380	0.8247	15
ABG	-0.7634	0.8378	-0.0743	20
BCG	-0.0840	-0.8666	0.9506	25
CAG	0.8812	-0.4617	-0.4194	30

Table -15: Output Fault values for fuzzy Classifier II

For Rf =200Ω				
Nature of fault	**S1**	**S2**	**S3**	**Fuzzy output**
AB	-0.781	0.8383	-0.056	35
BC	-0.094	-0.8765	0.9709	40
CA	0.952	-0.3206	-0.632	45
ABC	0.1733	-0.4849	0.3115	50

6. CONCLUSIONS

Protective relaying system is a versatile tool for protection of electric power systems. Because of the drastic changes occurring in power systems, the necessity for providing better protective relaying systems for transmission lines is essential. This work gives brief overview on different existing techniques for fault analysis and apart from the existing methodologies, a novel fault classification scheme is presented in this work. It uses post fault current samples of all the phases.

As discussed already a power system can be encountered with the faults named as AG, BG, CG, AB, BC, CA, ABG, BCG, CAG, ABC and ABCG phase fault. Hence it should be equipped suitably to tackle these faults in the most appropriate manner. Tackling these faults means to classify and finding out its location and graveness. In past on occurrence of fault, current is measured from either ends of the line which were then used in the algorithm to classify them. Since each fault react differently i.e. different characteristics of current when it occurs. 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

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