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# Fault Classification in Transmission Systems using Wavelet Transform

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#### Highlights

- Detection and classification of faults are extremely essential in power system.
- A novel fault detection technique is proposed for transmission line.
- Fault classification methodology is proposed using wavelet transform.
- The accuracy in fault classification was improved with proposed methodology.

#### Article Info

#### Abstract

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#### Keywords

Fault Fault classification Fuzzy inference system Wavelet transform Fault analysis is a prime apprehension in power system. This article elaborates an appropriate approach for detection of faults and wavelet technique is used for classification of faults in overhead lines. This method uses only measurements of post fault currents at single end of the line for fault analysis. To validate the efficacy of this method, simulations have been performed under various conditions of fault occurrence using MATLAB and the obtained outcomes are compared with fuzzy logic technique. The outcomes attained are promising and as well accuracy improved in classification.

# 1. INTRODUCTION

The populace on the earth is expanding step by step. Because of this the necessity of vitality in day by day life is steadily expanding. In this world, real number of issues is connected with populace. Power is the one of the fundamental requirements for survival to everybody on this planet. What's more, henceforth the interest for power is rising. It is a moving errand for power architects to give great eminence and un-intruded on capacity to the buyers. For most part the power system is isolated into four segments specifically, generation, transmission, dissemination and usage. In these transmission assumes a noteworthy job and it resembles a heart of the whole system and furthermore most extreme number of shortcomings happen in transmission systems.

The utmost way for transmission is the overhead lines and there is an impressive proportion of manners by which vitality is lost, concerning overhead lines. The reasons can be exterior or inside. In the outside reasons join lighting and catastrophes etc. These reason genuine interference in the power framework and that too constantly. Inside shortcomings consolidate the consonant problems to say the very least. Overhead lines are presented to air conditions [1], so the odds of shortcoming event are more. The dependability of the framework relies upon seriousness of the issue. Blames in overhead transmission lines are fundamentally characterized into two sorts, i.e. series and shunt. Series faultss are again ordered into two kinds, first sort is one open conductor issue and the other one is two open conductor issue. Contrasted with shunt

shortcomings, open conductor issues are in all respects infrequently happen. The most regularly happening shortcoming in transmission lines is short out deficiency. Once more, Short circuit flaws are characterized into two kinds they are symmetrical and unsymmetrical deficiencies [2]. The most much of the time happening flaw in transmission system is line to ground issue. Classification of faults is major task in fault analysis.

Soft computing technique plays a vital role in engineering domain. Over the years many better techniques emerged in the literature in the area of soft computing. In the power sector, soft computing techniques are useful for maximization of reliability in protective schemes, etc. The major techniques used are fuzzy logic [3,4],wavelet technique [5-7], artificial neural networks [8,9], neuro-fuzzy [10],wavelet-neural networks [11,12], wavelet-fuzzy [13], wavelet-neuro-fuzzy [14] and pattern-recognition method [15-17] for fault analysis. So as to group the issues, wavelet systems are comprehensively used to tackle complex security issues. This paper introduces an alternate strategy for deficiency grouping utilizing post issue flows near one side of the transmission line.

This first section contributes summary to faults in power transmission lines. Second section gives overview to wavelets. Third section describes the fault detection method. Section 4, gives fuzzy logic approach based fault classification. Section 5, enlightens the fault classification using wavelet method. Next section gives the outcomes in comparison with fuzzy logic and wavelet techniques for classification of faults and lastly, final section gives the conclusion of the work.

### 2. WAVELET

Wavelet procedure is a ground-breaking scientific instrument, valuable for preparing signals. Wavelet method fittingly picks a legitimate wavelet capacity called as mother wavelet and this chose capacity is broke down utilizing interpreted and scaled variants. Continuous wavelet transform (CWT) is characterized as pursues:

$$CWT_X(a,b) = \frac{1}{\sqrt{|a|}} \int x(t) \Psi\left(\frac{t-b}{a}\right) dt,$$
(1)

where x(t) is a function x(t),

a, b are dilation (scaling) and time shift (translation)parameters respectively,

 $\psi$  is mother wavelet function,

 $\frac{1}{\sqrt{|a|}}$  is for energy normalization across different scales.

Multi resolution analysis (MRA) is a standout amongst the instruments to dissect the low recurrence segment signals for long terms and high recurrence segment flag for brief lengths. Another best utilization of wavelet strategy is staggered decay. Sign can be deteriorated until an individual detail contains a solitary example by utilizing staggered decay. A discrete wavelet transform (DWT) is,

$$DWT_X(m,n) = \frac{1}{\sqrt{a_0^m}} \sum_l X(k) \Psi\left(\frac{n - la_0^m}{a_0^m}\right) dt.$$
<sup>(2)</sup>

Here  $a_0$  indicates fixed dilation step and m indicates dilation. Wavelet procedure has been in activity in parcel of various territories and gives an additional bit of leeway of less time reaction, which increases framework effectiveness.

### **3. FAULT DETECTION**

Detection is primary concern in analysis of faults. The considered system for the study is appeared in below Figure 1.



#### Figure 1. Power system

The following equation used of detection

Fault index ( $\emptyset$ ) = max ( $I_a$ +  $I_b$  +  $I_c$ ) Amp,

where  $I_a$ ,  $I_b$ ,  $I_c$  are currents of phase A, B & C respectively. For ground fault, fault index (Ø) value exceeds the value 100 and during phase faults will be lesser than the 1. There are three types of transmission lines.

#### i) Short transmission line (STL) model

The transmission line which has a length of 80 km or lesser are generally referred as short transmission lines. A 3 phase system model which consists of 20 kV source voltage, load angle of  $20^{\circ}$ , fault resistance of 50  $\Omega$  with a 75 km line is considered.

# ii) Medium transmission line (MTL) model

The transmission line which has an effective length of more than 80 km but less than 250 km is usually considered to as a medium transmission line. A 3 phase system model which consists of 100 kV source voltage, load angle of  $20^{\circ}$ , fault resistance of 100  $\Omega$  with a 160 km line is considered.

#### iii) Long transmission line (LTL) model

A power transmission line which has an effective length of 250 km or above is considered as a LTL. A 3 phase system model which consists of 400 kV source voltage, load angle of 20<sup>0</sup>, fault resistance of 100  $\Omega$  with a 500 km line is considered. From Table 1 and Table 2, it can be understood that different types of phase faults are applied to all the considered cases (short, medium and long transmission lines) to test the accuracy of the presented approach. From Table 1 it can be understood that all the fault index values are greater than 100 which means that the proposed fault detection technique successfully detects any type of ground faults. Table 2 deals with detection of phase faults. According to the presented technique the occurrence of phase fault can be found, if the fault index value less than 1. In Table 2 it can be understood that all the  $\emptyset$  values are less than 1, which means that the proposed fault detection technique successfully detects dud that all the  $\emptyset$  values are less than 1. Which means that the proposed fault detection technique successfully detects any type of that all the  $\emptyset$  values are less than 1. Which means that the proposed fault detection technique successfully detects any type of phase faults.

*Table 1.* Ø for ground faults

Foult	for STL Model	for MTL Model	for LTL Model
Гаин	Ø (Amps)	Ø (Amps)	Ø (Amps)
AG	158.7601	384.8914	1.3324e+03
BG	159.5459	387.1372	1.3248e+03
CG	158.7642	380.4979	1.3215e+03
ABG	149.9515	362.1008	1.0780e+03
BCG	149.0631	356.1164	1.0729e+03
CAG	158.2238	365.0298	1.0883e+03

#### Table 2. Ø for phase faults

Foult	for STL Model	for MTL Model	for LTL Model
Гаш	Ø (Amps)	Ø (Amps)	Ø (Amps)
AB	0.0058	0.0220	0.1156
BC	0.0047	0.0220	0.1032
CA	0.0078	0.0278	0.1437
ABC	0.0050	0.0222	0.0440

(3)

#### 4. FAULT CLASSIFICATION USING FUZZY-LOGIC TECHNIQUE

The over-all procedure executed based on fuzzy logic method is appeared in below Figure 2.



Figure 2. Fuzzy system

 $S_1$ ,  $S_2$  and  $S_3$  in Figure 2, are inputs to the fuzzy system and F is the output variable. Calculation [3] of these input variables using currents are given below. The ratios  $P_1$ ,  $P_2$  and  $P_3$  are determined using currents and is as follows:

$$P_{1} = \frac{\max\{abs(I_{a})\}}{\max\{abs(I_{b})\}}, P_{2} = \frac{\max\{abs(I_{b})\}}{\max\{abs(I_{c})\}}, P_{3} = \frac{\max\{abs(I_{c})\}}{\max\{abs(I_{a})\}}$$
(4)

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

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

$$S_1 = P_1(n) - P_2(n), S_2 = P_2(n) - P_3(n), S_3 = P_3(n) - P_1(n)$$
(6)

 $S_1$ ,  $S_2$  and  $S_3$  are inputs to the FIS and output of the FIS denoted with F. The proposed FIS is shown in Figure 3. Three triangular membership functions are chosen for each input and designated as  $Small_g$  with membership function ranging between -1.0 and -0.005, Medium<sub>g</sub> with membership function ranging between 0.02 and 0.3 and Large<sub>g</sub> with membership function ranging between 0.2 and 1.0 for ground faults,  $Small_{ph}$  with membership function ranging between -1.0 and -0.005, Medium<sub>ph</sub> with membership function ranging between 0.01 and 0.6 and Large<sub>ph</sub> with membership function ranging between 0.5 and 1.0 for phase faults. Figure 4 and Figure 5 gives membership range for both inputs and output respectively. Fault output variables appeared in Table 3. The fuzzy if-then rules used for fault classification are mentioned in Table 4.



Figure 3. Fuzzy inference system

 uble 5. Outputs for fuzzy inference system										
Fault	AG	BG	CG	ABG	BCG	CAG	AB	BC	CA	ABC
Output (F)	5	10	15	20	25	30	35	40	45	50

Table 3. Outputs for fuzzy inference system

	Output			
$\mathbf{S}_1$	$S_2$	<b>S</b> <sub>3</sub>	Output	
Largeg	Medium <sub>g</sub>	Small <sub>g</sub>	AG	
Small <sub>g</sub>	Largeg	Medium <sub>g</sub>	BG	
Medium <sub>g</sub>	Small <sub>g</sub>	Largeg	CG	
Small <sub>g</sub>	Largeg	Small <sub>g</sub>	ABG	
Small <sub>g</sub>	Small <sub>g</sub>	Largeg	BCG	
Largeg	Small <sub>g</sub>	Small <sub>g</sub>	CAG	
Small <sub>ph</sub>	Large <sub>ph</sub>	Small <sub>ph</sub>	AB	
Small <sub>ph</sub>	Small <sub>ph</sub>	Large <sub>ph</sub>	BC	
Large <sub>ph</sub>	Small <sub>ph</sub>	Small <sub>ph</sub>	CA	
Medium <sub>ph</sub>	Medium <sub>ph</sub>	Small <sub>ph</sub>	ABC	
Small <sub>ph</sub>	Medium <sub>ph</sub>	Medium <sub>ph</sub>	ABC	
Medium <sub>ph</sub>	Small <sub>ph</sub>	Medium <sub>ph</sub>	ABC	
Small <sub>ph</sub>	Small <sub>ph</sub>	Medium <sub>ph</sub>	ABC	
Medium <sub>ph</sub>	Small <sub>ph</sub>	Small <sub>ph</sub>	ABC	
Small <sub>ph</sub>	Medium <sub>ph</sub>	Small <sub>ph</sub>	ABC	

Table 4. Rules for fault classification using values of  $S_1$ ,  $S_2$  and  $S_3$ 



Figure 4. Input membership function plots



Figure 5. Output membership function plots

The validation of the results obtained for fault classification using fuzzy logic technique for different transmission line models is presented in the Table 5, 6 and 7.

S No	Applied	S	S.	S.	Fuzzy	Discovered
5.NO.	fault	$\mathbf{S}_1$	$\mathbf{S}_2$	<b>D</b> 3	output	fault
1	AG	0.9704	0.0286	-0.9990	5.1	AG
2	BG	-0.9986	0.9626	0.0360	9.9000	BG
3	CG	0.0164	-0.9987	0.9823	30	CAG
4	ABG	-0.9596	0.9976	-0.0380	29.3308	CAG
5	BCG	-0.0398	-0.9576	0.9974	34.1308	AB
6	CAG	0.9988	-0.0278	-0.9710	39.2308	BC
7	AB	-0.9830	0.9997	-0.0167	29.3308	CAG
8	BC	-0.0167	-0.9830	0.9997	34.1308	AB
9	CA	0.9997	-0.0167	-0.9830	39.2308	BC
10	ABC	-1.0965e-04	-9.2380e-05	2.0203e-04	30	CAG

*Table 5. Validation of fuzzy logic technique for STL model* 

 Table 6. Validation of fuzzy logic technique for MTL model

S No	Applied	$\mathbf{S}_1$	$\mathbf{S}_2$	S.	Fuzzy	Discovered
5.INO.	fault			33	output	fault
1	AG	0.9112	0.0789	-0.9901	5.1000	AG
2	BG	-0.9861	0.8383	0.1478	9.9000	BG
3	CG	0.0847	-0.9883	0.9037	15	CG
4	ABG	-0.8855	0.9813	-0.0958	29.3308	CAG
5	BCG	-0.1043	-0.8747	0.9789	34.1308	AB
6	CAG	0.9871	-0.0801	-0.9071	39.2308	BC
7	AB	-0.9191	0.9947	-0.0756	29.3308	CAG
8	BC	-0.0762	-0.9184	0.9946	34.1308	AB
9	CA	0.9946	-0.0768	-0.9178	39.2308	BC
10	ABC	-0.0967	0.0495	0.0472	50.1000	ABC

 Table 7. Validation of fuzzy logic technique for LTL model

S No	Applied	S.	S.	S.	Fuzzy	Discovered
5.110.	fault	51	52	53	output	fault
1	AG	0.6839	0.2022	-0.8861	5.0805	AG
2	BG	-0.8511	0.5334	0.3176	50.0845	ABC
3	CG	0.2028	-0.8976	0.6948	15	CG
4	ABG	-0.7421	0.9089	-0.1669	28.3318	CAG
5	BCG	-0.1674	-0.7410	0.9084	33.2247	AB
6	CAG	0.9020	-0.1585	-0.7434	38.3795	BC
7	AB	-0.6323	0.9358	-0.3035	28.8881	CAG
8	BC	-0.2875	-0.6519	0.9394	33.8197	AB
9	CA	0.9359	-0.3036	-0.6322	39.2308	BC
10	ABC	-0.0048	4.9725e-04	0.0043	30	CAG

#### 5. FAULT CLASSIFICATION USING WAVELET TECHNIQUE

This approach uses DWT with MRA for fault classification. By calculating the norm of the detail coefficients for all currents, the fault classification can be achieved. For phases A, B and C assume that P, Q, R is the maximum value of norm of the detail coefficients respectively. The norm calculation is

$$\|D1\| = \left[\sum_{k=1}^{n_d} |D1(k)|\right]^{1/2}.$$
(7)

If P, Q & R for any phase crosses the threshold value (th) then it represents the occurrence of fault in a particular phase. For example, if the Q value exceeds the threshold value, there is an occurrence of fault in phase B. This method is tested for all transmission lines. Based on outputs of plenty simulations the

threshold values (th) for STL, MTL and LTL models are considered as 0.085, 0.175 and 0.5 respectively. To observe the performance of proposed technique simulations under various fault types have been performed in MATLAB. Table 8 deals with classification of all type of faults for STL. From the table it can be understood that various faults are applied to the system to find the accuracy of this approach. In Table 8, P, Q and R are the computed outputs, which are useful to classify the nature of faults. According to the presented technique the occurrence of fault is true whenever the obtained output values are greater than the threshold values. If P is greater than the th it represents the phase A is faulted. The threshold value for STL is 0.085 and hence for any value greater than 0.085 indicates the abnormality in that particular phase, which is can be observed in Table 8. The results of proposed method all type faults for STL have been presented in the Table 8 and for MTL have been presented in the Table 9 and for LTL have been presented in the Table 10.

	anteiente	m of man	erer reenn	ique joi .	JI B model			
S.No.	Appli ed fault	Р	Q	R	is P >th (Yes or No)	is Q >th (Yes or No)	is R >th (Yes or No)	Discovered fault
1	AG	0.2500	0.0492	0.0467	Yes	No	No	AG
2	BG	0.0527	0.2500	0.0459	No	Yes	No	BG
3	CG	0.0486	0.0530	0.2499	No	No	Yes	CG
4	ABG	0.2456	0.2617	0.0806	Yes	Yes	No	ABG
5	BCG	0.0816	0.2457	0.2615	No	Yes	Yes	BCG
6	CAG	0.2617	0.0560	0.2456	Yes	No	Yes	CAG
7	AB	0.2406	0.2386	0.0308	Yes	Yes	No	AB
8	BC	0.0308	0.2407	0.2387	No	Yes	Yes	BC
9	CA	0.2387	0.0308	0.2406	Yes	No	Yes	CA
10	ABC	0.2574	0.2576	0.2576	Yes	Yes	Yes	ABC

 Table 8. Validation of wavelet technique for STL model

 Table 9. Validation of wavelet technique for MTL model

S.No.	Appli ed fault	Р	Q	R	is P >th (Yes or No)	is Q >th (Yes or No)	is R >th (Yes or No)	Discovered fault
1	AG	0.3859	0.1114	0.1148	Yes	No	No	AG
2	BG	0.1244	0.3860	0.1208	No	Yes	No	BG
3	CG	0.1254	0.1146	0.3861	No	No	Yes	CG
4	ABG	0.3803	0.4049	0.1636	Yes	Yes	No	ABG
5	BCG	0.1709	0.3805	0.4050	No	Yes	Yes	BCG
6	CAG	0.4049	0.1431	0.3804	Yes	No	Yes	CAG
7	AB	0.3785	0.3649	0.1009	Yes	Yes	No	AB
8	BC	0.1009	0.3782	0.3647	No	Yes	Yes	BC
9	CA	0.3650	0.1008	0.3786	Yes	No	Yes	CA
10	ABC	0.3995	0.3994	0.3993	Yes	Yes	Yes	ABC

	Table 10.	Validation	of wavelet	technique	for LTL	model
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S.No.	Appli ed fault	Р	Q	R	is P >th (Yes or No)	is Q >th (Yes or No)	is R >th (Yes or No)	Discovered fault
1	AG	0.6730	0.4055	0.3929	Yes	No	No	AG
2	BG	0.3905	0.6728	0.4240	No	Yes	No	BG
3	CG	0.4295	0.4093	0.6729	No	No	Yes	CG
4	ABG	0.7155	0.7630	0.4024	Yes	Yes	No	ABG
5	BCG	0.4110	0.7158	0.7631	No	Yes	Yes	BCG
6	CAG	0.7661	0.3889	0.7154	Yes	No	Yes	CAG
7	AB	0.7632	0.6736	0.3613	Yes	Yes	No	AB
8	BC	0.3613	0.7639	0.6745	No	Yes	Yes	BC

9	CA	0.7020	0.3616	0.7734	Yes	No	Yes	CA
10	ABC	0.7743	0.7739	0.7743	Yes	Yes	Yes	ABC

The Figure 6 shows the norm coefficients of for LTL. In this Figure 6, norm coefficients of phase A, B and C currents are denoted with blue, green and red colours respectively. From this figure it can observed that the P exceeds the th of LTL which indicates the occurrence of fault in phases A, where as in Figure 7 Qand R exceeds the th, which indicates the occurrence of fault in phases B and C. Similarly the occurrence of AB and ABC faults can be seen in Figure 8 and 9, respectively.



# 6. COMPARISON

The results in section 4 and section 5 indicate that fuzzy logic technique misclassifies the faults in each transmission line model and wavelet technique succeeded to classify the faults. The outcomes of fuzzy logic and proposed wavelet technique is compared and presented in Table 11 for different transmission line models.

S.No.	Applied fault	Discovered f	ault for STL	Discovered fault for MTL		Discovered fault for LTL	
		Fuzzy logic	Wavelet	Fuzzy logic	Wavelet	Fuzzy logic	Wavelet
		teeninque	teeninque	teeninque	teeninque	teeninque	teeninque
1	AG	AG	AG	AG	AG	AG	AG
2	BG	BG	BG	BG	BG	ABC	BG
3	CG	CAG	CG	CG	CG	CG	CG

Table 11. Comparison of fuzzy logic and wavelet techniques for STL, MTL and LTL models

4	ABG	CAG	ABG	CAG	ABG	CAG	ABG
5	BCG	AB	BCG	AB	BCG	AB	BCG
6	CAG	BC	CAG	BC	CAG	BC	CAG
7	AB	CAG	AB	CAG	AB	CAG	AB
8	BC	AB	BC	AB	BC	AB	BC
9	CA	BC	CA	BC	CA	BC	CA
10	ABC	CAG	ABC	ABC	ABC	CAG	ABC

### 7. CONCLUSION

This work presents a fault detection technique using fault index ( $\emptyset$ ) and fault classification technique using DWT. The robustness of the proposed technique has been tested and also outcomes of the wavelet technique are compared with fuzzy logic technique on different types of transmission line models (STL, MTL and LTL). The fuzzy logic approach misclassifies the faults in all models but the proposed wavelet technique classifies the faults exactly. According to the results obtained the success rate of the fuzzy logic technique performs comparatively better for MTL model and is at a minimum performance level for both STL and LTL models which is not encouraging. On the other hand looking at the proposed wavelet technique the success rate is about 100% for all type of faults in any transmission models which is very significant and challenging and so the proposed method can be used in real time applications for fault monitoring in power systems.

### **CONFLICTS OF INTEREST**

No conflict of interest was declared by the authors.

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