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Fault identification in electrical power distribution system using combined discrete wavelet transform and fuzzy logic

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Abstract

In this proposed work a fuzzy logic based algorithm using discrete wavelet transform is developed for identifying the various faults in the electrical distribution system for an unbalanced distribution electrical power system. This technique is capable to identify the ten different types of faults with negligible effect of variation in fault inception angle, loading and other parameters of the power distribution system. The proposed method is tested on IEEE 13 bus electrical distribution system and on an Indian scenario of distribution system. The current of respective three phases is used as input signal for fault identification and the results obtained from the proposed method are more than satisfactory.

Keywords: Fault identification; Fuzzy logic; Discrete wavelet transform; Fault inception angle

1. Introduction

Nowadays, distribution systems carry a large amount of power as compared to earlier era because of increase in per capital consumption of electricity. Any, change is not predicted in the present trend in near future and it will sustain for decades at least in India and in other developing countries. So, any disturbance in the power supply may lead to discontinuation of power supply and degradation in the power quality. Distribution system is the most vital component in terms of its effect on reliability, quality of service, cost of electricity and aesthetic impact on society. In any industrialized country, the distribution system delivers electricity literally everywhere taking power from different generating station to the end users. Two foremost things which are required for quick restoration of the faulty part are fault location and type of fault. Similarly, in digital distance protection system the appropriate operation of protective device and accurate classification of the fault are necessary (Grainger and Stevenson, 1994).

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By seeing the above mentioned benefits of fault type identification a lot of research work is carried out (Aggrawal et al., 1999; Lin et al., 2001; Ferrero et al., 1995; Wang and Keerthipala, 1998; Girgis and Johns, 1989; Protopapas et al., 1991; Togami et al., 1995; Chen et al., 2000; Adu, 2002). Previously, a large amount of research work has been done in the electrical transmission system as they carry large amount of power and any disturbance on the transmission system will affect the whole power system. Nowadays, distribution system is also carrying a large amount of power due to increase in urbanization and industrialization in developing country like India. Moreover the use of underground cable also increases the complexity in fault identification. So, distribution system fault type identification is becoming much more important.

Although, a large number of techniques are available for fault identification and classification. Some of them are based upon continuous monitoring of (1) Voltage, (2) Current, (3) Impedance, *etc.* All these techniques have their own advantages and disadvantages (Alanzi et al., 2014).

Some intelligent techniques, (generally known as knowledge based techniques) of the fault classification in transmission line are based upon Neural Network (Aggrawal et al., 1999; Lin et al., 2001); Fuzzy Logic and Fuzzy Neural Network (Ferrero et al., 1995; Wang and Keerthipala, 1998); and knowledge system based approach (Girgis and Johns, 1989; Protopapas et al., 1991). All these techniques suffer from a major drawback that a proper training is required for neural network and these are not susceptible to high impedance faults. Most of the research work has been done for identifying the various types of fault *i.e.* whether the fault is line to ground, double line to ground, double line fault or three phase fault. Recently, the phase angle classification and fuzzy logic based schemes (Das, 2006) have been published in the research papers. A major drawback of the angle based method is that its accuracy is only about 60%. Other techniques such as the under-impedance and torque technique utilize the positive and zero sequence impedances of the electrical transmission line. But the zero sequence impedance of the transmission line cannot be determined precisely and are therefore, suitable for distance relays where the reach of the relays is defined. A fault recorder, however, is able to monitor all transmission lines emanating from a station and possibly most of the adjoining lines. Furthermore, the under-impedance and torque algorithms are sensitive to close-in faults with strong sources behind them. It is possible that for such fault conditions more than one measuring unit would estimate either the positive sequence fault impedance or the effective operating torque is close to the desired value. These techniques, therefore, cannot be reliably depended upon to determine the faulted phases under all fault conditions.

An angle based fault classification approach (Das, 2006) possesses a better benefit as the difference of load current and the fault current. Moreover the use of fuzzy logic provides greater flexibility for fault classification, but removing the decaying fault current component from the load current is very difficult and generally fuzzy membership function overlapping provides poor results. Multi Resolution Wavelet Transform algorithm (Gayatri et al., 2007) is very fast and accurate in classification of fault, but the main drawback is that it only identifies the type of fault *i.e.* LG, LL, LLG and three phase fault.

The proposed scheme of fault classification is more accurate as it can easily classify the ten different types of fault *i.e.* three types of line to ground fault, three types of double line to ground fault, three line to line fault and a three phase symmetrical fault. The main benefit of proposed scheme is that only three phase line current measurement is needed and no other parameter or information *e.g.* circuit breaker (CB) position and isolator is required. The developed method is tested on IEEE 13 bus distribution system and on Indian power distribution utility. All the signal analysis, distribution system model simulation and fuzzy logic system are designed in MATLAB®/SIMULINK environment.

2. Fault identification strategy

Fault identification strategy is achieved by implementing the discrete wavelet transform. The discrete wavelet transform is used to calculate the change in energy of a particular energy level of measured current signals. The energies calculated from discrete wavelet transform are then uses as inputs into the fuzzy logic system.

2.1. Discrete wavelet transform

The wavelet transform is a tested tool for analyzing and studying the signals effectively (Rizwan et al., 2013). The wavelet transform resolves the measured distorted signal into different time–frequency domains (Jamil et al., 2014). Wavelet transform uses the expansion and contraction of basis functions to detect various frequency components in the measured signal. Wavelet transform decomposes the signal into different band of frequencies. The basis function

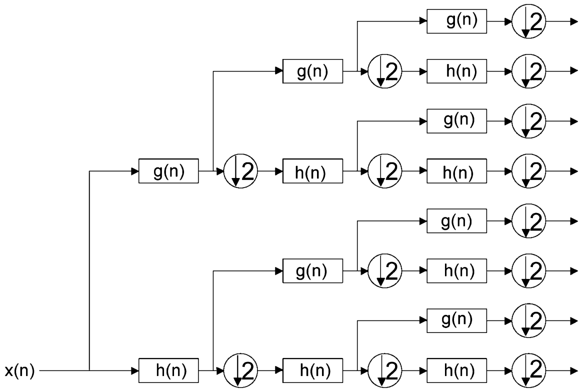

Fig. 1. Multi-level decomposition of signal $X[n]$.

is mother wavelet, which uses the dilation and translation property. Here, large windows are used to obtain the low frequency component of the signal, while small window reflect discontinuities.

$$Wf(m,n) = 2^{(-m/2)} \int f(t)\Phi(2^{-m}t - n)\,dt \tag{1}$$

where m is frequency and n is time. In practice wavelet series is given by

$$f(t) = \sum_{k=-\infty}^{k=\infty} c_k\Phi(t-k) + \sum_{k=-\infty}\sum_{k=-\infty}^{\infty} d_{ik}\Phi(2^i t - k) \tag{2}$$

$$\Phi(x) = \sqrt{2}\sum_n h_0\Phi(2x-n) \tag{3}$$

where $\Phi(x)$ is scale function and h_0 is the low pass filter coefficient.

$$\Phi(x) = \sqrt{2}\sum_n h_1\Phi(2x-n) \tag{4}$$

where $\Phi(x)$ is wavelet function and h_1 is high pass filter coefficient. In Fig. 1 various decomposition levels of wavelet tree are shown, where $X[n]$ is the discrete signal.

The decomposition levels can be classified into detail and approximate coefficients. The various details and approximate coefficient contain different energies at different level of decomposed signal. These energies can be calculated easily and on the basis of these energies faults can be classified easily.

The energy content of any decomposed signal is given by the following formula:

$$E = \sum |x|^2 \tag{5}$$

where x is the wavelet coefficients at decomposition level.

The proposed discrete wavelet transform is performed on IEEE 13 bus shown in Fig. 2 (Kirsting, 1991).

Let us consider the fault on bus number 633, the various currents and voltages waveforms of the faulted system at the substation are shown in Fig. 3. The wavelet coefficient and hence the various energies associated with the signals are calculated and results obtained during the fault are shown in Tables 1 and 2.

2.2. *Fuzzy logic*

It can be observed from Table 2, that the energies obtained are fuzzy in nature. Therefore, fuzzy logic is used for fault identification to differentiate the type of fault. Fuzzy logic system possesses certain benefits over neural network. The fuzzy logic system works on by simply defining certain rules and results can be obtained, but in neural network a rigorous training is required. Besides there is convergence of the algorithm is also a problem.

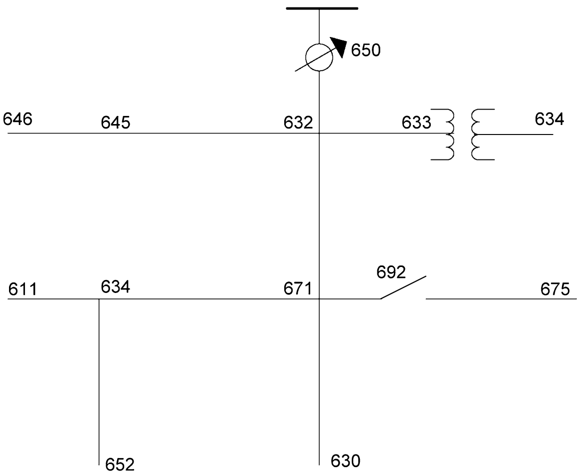

Fig. 2. IEEE 13 bus system.

Table 1
Typical value of the different energies.

Type of fault	Energy_A ($\times 10^{11}$)	Energy_B ($\times 10^{11}$)	Energy_C ($\times 10^{11}$)	Energy_G ($\times 10^{11}$)
A-G	1.342	0.0014	0.0019	0.1091
B-G	0.0028	1.3278	0.0018	0.1097
C-G	0.0025	0.0016	1.3425	0.1142
A-B	1.9717	1.8868	0.0015	0
B-C	0.0021	1.9774	1.9014	0
C-A	1.9183	0.0012	2.0119	0
A-B-G	2.1714	2.0964	0.002	0.0688
B-C-G	0.0028	2.1633	2.1246	0.0663
C-A-G	2.1382	0.0016	2.194	0.0673
A-B-C	2.5991	2.5649	2.6127	0

Table 2
Typical value of normalized energy (fuzzy inputs).

Type of fault	Energy_A	Energy_B	Energy_C	Energy_G
A-G	1	0.0010	0.0014	0.0905
B-G	0.0021	1	0.0013	0.0913
C-G	0.0019	0.0012	1	0.0934
A-B	0.9252	1	0.0010	0.0073
B-C	0.0151	1	0.9535	0.0013
C-A	0.9502	0.0006	1	0
A-B-G	1	0.9710	0.0009	0.0345
B-C-G	0.0013	1	0.9739	0.0339
C-A-G	0.9774	0.0007	1	0.0344
A-B-C	0.9991	0.9941	1	0

In the proposed method the approximations are involved, the different inputs or the antecedents are represented by an appropriate corresponding fuzzy variable. As the antecedent parts are variables which are fuzzy in nature, the other variables in the remaining resultant parts should be fuzzy in nature. The above approximate rule base system is actually a "Fuzzy Rule Base System." The triangular membership function has been used to represent all these fuzzy variables (in both antecedent and consequent parts of the fuzzy rules), in this proposed work. This fault classification model uses the triangular membership function, as shown in Fig. 4. All the four inputs are fed through by using four triangular membership functions.

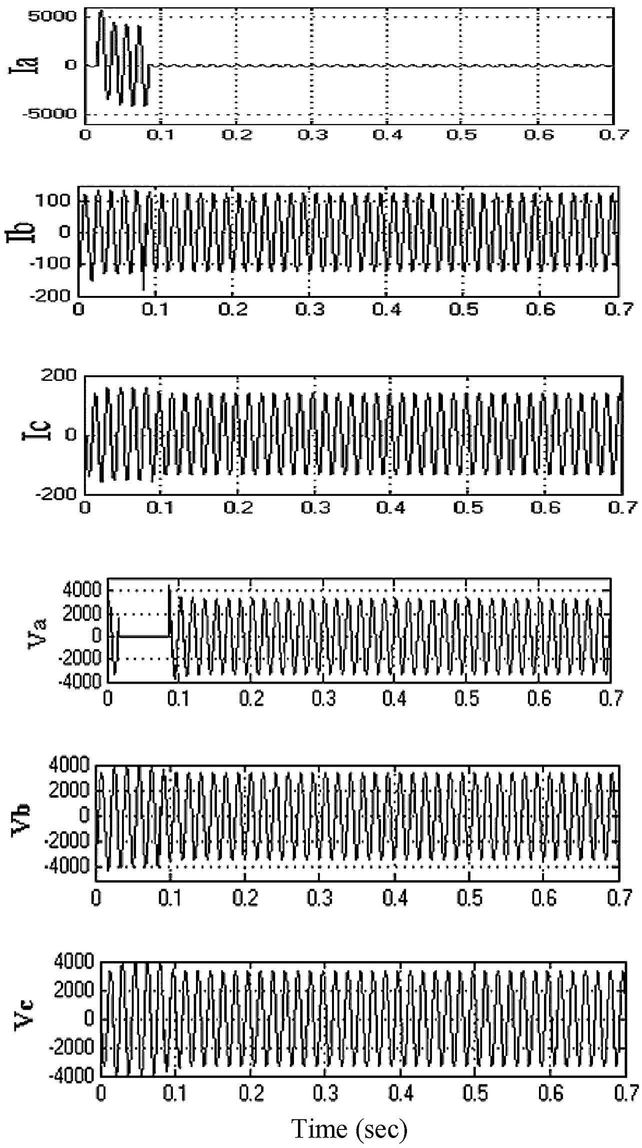

Fig. 3. Current and voltage waveform during fault at bus 633.

The values of three edges of triangle for all ten types of fault have been taken in such a manner that the triangular membership function corresponds to any particular type of fault, and is symmetric about the taken decimal number. This can be confirmed from Table 3. Thus, the different three edges which have been assigned to represent the fuzzy fault types are shown in Table 4.

In Table 3, B3 represents phase-A, B2 represents phase-B, B1 represents phase-C and B0 represents the ground. The appropriate three edges are calculated for showing the fuzzy variables for declaring the different types of fault. The method for selecting the three edges is as follows. In the beginning, in order to represent the type of fault correctly, a binary logic system is developed. In this coding system, a four digit binary number (B3B2B1B0) is generated to represent the types of fault. The complete chart containing the binary numbers with respect to each type of fault and their corresponding equivalent decimal numbers are shown in Table 3. These rules are used in output of fuzzy system.

The fuzzy logic developed as scheme shown in Fig. 5 is used for applying the proposed method.

The crisp inputs are four in number which are the normalized energies of the measured currents of phase A, phase B, phase C and zero sequence current respectively. They are calculated from the sampled values of the during-fault

Table 3
Fault code table.

Fault type	B3	B2	B1	B0	Equivalent decimal number
A-G	1	0	0	1	9
B-G	0	1	0	1	5
C-G	0	0	1	0	3
A-B	1	1	0	0	12
B-C	0	1	1	0	6
C-A	1	0	1	0	10
A-B-G	1	1	0	1	13
B-C-G	0	1	1	1	7
C-A-G	1	0	1	1	11
A-B-C	1	1	1	1	15

Table 4
Fuzzy variable for representation of different types of fault.

Fault types	Triplets		
	A	B	C
A-G	8.5	9	9.5
B-G	4.5	5	5.5
C-G	2.5	3	3.5
A-B	11.5	12	12.5
B-C	5.5	6	6.5
C-A	9.5	10	10.5
A-B-G	12.5	13	13.5
B-C-G	6.5	7	7.5
C-A-G	10.5	11	11.5
A-B-C	14.5	15	15.5

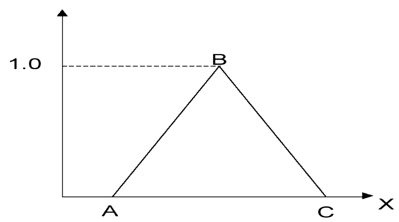

Fig. 4. Triangular membership function.

currents of respective three phases *i.e.* phase A, phase B and phase C. Because, the values are crisp in nature; they are then needed to be converted into their corresponding fuzzy variables. In this paper the singleton fuzzifier (Mendel, 1995) has been adopted for the fuzzification of the assigned values.

After fuzzification, the fuzzified inputs are used to detect the fault and used as inputs to the Fuzzy Inference System (FIS). The FIS based upon the proposed fuzzy rules, classifies the appropriate types of fault as its output. The output

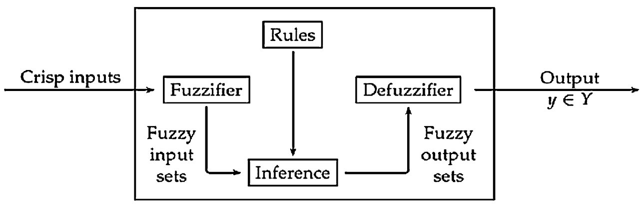

Fig. 5. FLS for fault classification.

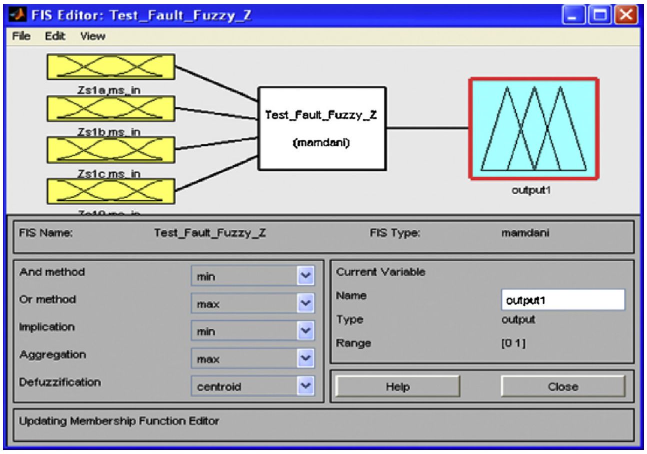

Fig. 6. Typical FIS Editor of Fuzzy Logic Tool Box in MATLAB®.

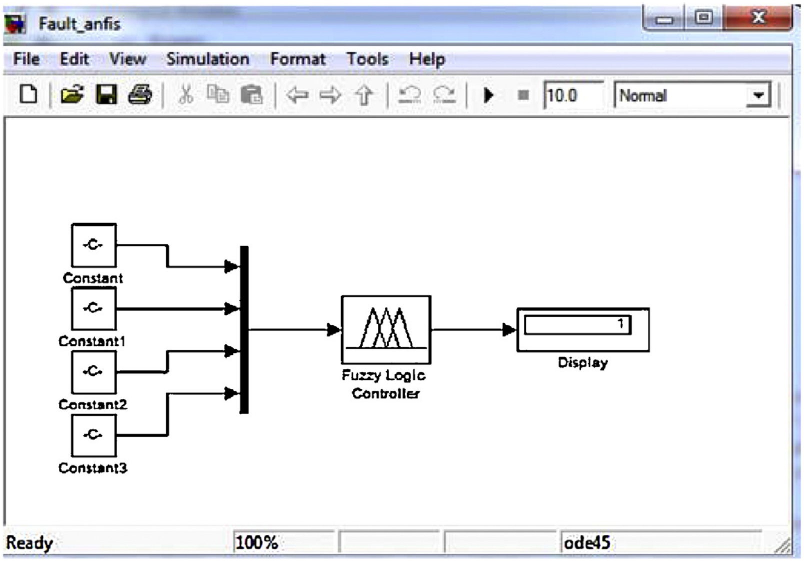

Fig. 7. Simulink model of FIS in MATLAB®.

of the inference system is also fuzzy in nature. These fuzzy outputs directly cannot be used to declare the fault, but first needed to be defuzzified to determine actual type of the fault correctly. The Centroid Defuzzification function has been implemented for developing the purposed FIS. The simulation of the FLS method has been carried out in the Fuzzy Logic Toolbox of the MATLAB®/Simulink software (as shown in Fig. 6) (Matlab, 2015). The simulink model of developed FIS system in MATLAB® is shown in Fig. 7.

The rules for the given four inputs corresponding to the energy levels of four currents to obtain the result are as follows:

1. If Energy_A is “near about 1” and Energy_B is “near about 0” and Energy_C is “near about 0” and Energy_G is “near about 1” then the fault type is “A-G”.
2. If Energy_A is “near about 1” and Energy_B is “near about 1” and Energy_C is “near about 0” and Energy_G is “near about 0” then the fault type is “A-B”.
3. If Energy_A is “near about 1” and Energy_B is “near about 1” and Energy_C is “near about 0” and Energy_G is “near about 1” then the fault type is “A-B-G”.

Table 5
FLS output for different fault at bus 633.

Type of fault at bus 633	Fuzzy output
A-G	9.52
B-G	5.52
C-G	3.44
A-B	12.5
B-C	6.5
C-A	10.5
A-B-G	13.5
B-C-G	7.44
C-A-G	11.4
A-B-C	15.5

Table 6
FLS output for fault at different bus IEEE 13 bus system.

Bus no.	Types of fault									
	A-G	B-G	C-G	A-B	B-C	C-A	A-B-G	B-C-G	C-A-G	Three phase fault
671	9.52	5.52	3.44	12.5	6.5	10.5	13.5	7.44	11.4	15.5
634	9.5225	5.5265	3.412	12.5	6.5	10.5	13.5	7.44	11.4	15.5

4. If Energy_A is "near about 1" and Energy_B is "near about 1" and Energy_C is "near about 1" and Energy_G is "near about 1" then the fault type is "symmetrical".

The different ten types of faults are being simulated by using different values of Rf and Fault Inception Angle (FIA). The results using different values of Rf and Fault Inception Angle (FIA) obtained are almost similar, as only the change in energy is measured. Hence, it is independent for different values of FIA. The typical output of FLS for different faults at IEEE 13 bus radial distribution system at bus 633 is shown in Table 5.

3. Results and discussion

The proposed algorithm is tested using the simulated as well as real time data. The different sources for the test data are

1) MATLAB generated data.
2) IEEE 13 bus radial distribution feeder.
3) Fault data of distribution system of Janpur (M.P., India) provided by MIPOWER Company (shown in Fig. 8).

For a fault at bus P27 the various results are shown in Table 6 and the corresponding value of the fuzzy output is also shown in Table 7.

A fault detection system based on fuzzy logic and discrete wavelet transform has been designed in this work. This design is validated on IEEE 13 bus radial distribution system and radial power distribution network using real time

Table 7
FLS output for fault at different bus: distribution system, Janpur (M.P., India).

Bus no.	Type of fault									
	A-G	B-G	C-G	A-B	B-C	C-A	A-B-G	B-C-G	C-A-G	Three phase fault
P25	9.02	5.18	3.30	11.87	6.5	10.45	12.85	7.12	11.38	15.45
P31	9.1416	5.1949	3.2755	12.05	6.5	10.4546	12.84	7.25	11.36	15.65

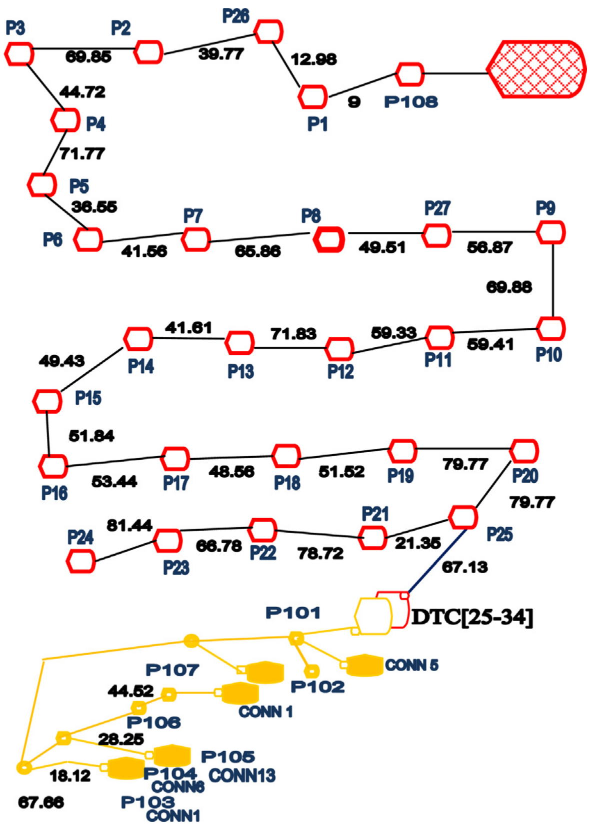

Fig. 8. SLD of distribution system, Janpur (M.P., India).

data and MATLAB®/Simulink software. The values of energies for different types of faults are shown in Table 8. The final results of FLS are very precise and shown in Table 9. It is able to detect all the ten types of faults *i.e.* A-G, B-G, C-G, A-B, B-C, C-A, A-B-G, B-C-G, C-A-G and three phase symmetrical fault. It has been found that faults could occur in radial distribution systems with all possible combinations; hence the importance of the fuzzy membership functions in declaring the various types of fault is proved. The simplicity of the design based on the fuzzy logic, means a drastic reduction in load loss and energy loss on distribution systems due to prolonged outages leading to longer feeder downtime during faulted conditions. The various conclusions and results drawn from the study are:

Table 8
Typical values of normalized energy: Janpur (M.P., India).

Type of fault	Energy_A	Energy_B	Energy_C	Energy_G
A-G	1	0.1174	0.0911	0.0724
B-G	0.0955	1	0.1234	0.079
C-G	0.121	0.0922	1	0.077
A-B	1	0.6007	0.2670	0
B-C	0.2738	1	0.6127	0
C-A	0.6196	0.2634	1	0
A-B-G	0.8536	1	0.0176	0.2172
B-C-G	0.0178	0.8306	1	0.2136
C-A-G	1	0.0171	0.8174	0.2150
A-B-C	1	0.9753	0.9811	0

Table 9
FLS output for different fault at bus P27.

Type of fault at bus P27	Fuzzy output
A-G	9.52
B-G	5.52
C-G	3.44
A-B	12.5
B-C	6.5
C-A	10.5
A-B-G	13.5
B-C-G	7.44
C-A-G	11.4
A-B-C	15.5

1) The proposed method has accuracy of around 95% for the lightly unbalanced system (*i.e.* for less unbalanced system).
2) The proposed method provides good results for different values of FIA and it independent of FIA variations.
3) For sake of accuracy the 8 level symlet mother wavelet is used.
4) The proposed algorithm has fuzzy membership function which adapt according to the experimental results obtained.

4. Conclusion

The operating conditions and electrical parameters in an electrical power distribution system vary over a wide range because of dynamic nature of the power system and diverse nature of load. The structure of any electrical power distribution system often changes because of the changing of load patterns, switching of power system equipments, sudden break down of generating units, *etc*. The fault resistance, fault inception angle and different loading conditions of electrical power distribution system also affect the performance of any fault detection and classification method.

The proposed method is found to be quite satisfactory in classification of fault types for both the distribution systems *i.e.* for IEEE 13 bus system and for utility distribution system Janpur, Madhya Pradesh (India). But the space constraint forced us to show the results of the fault that occur at the bus 633. The proposed method is fully effective in classifying all ten types of faults and for any possible combination of different power system parameters. The fault inception angle considered for the proposed research is 0.9^0 and the value of fault resistance is $0\,\Omega$. The results of the proposed method are not affected by different values of FIAs, fault resistance and other distribution parameters. The observation of the results (as shown in Table 2) shows that the values of the normalized energies of respective three phases are crisp in nature and usually varies from 0 to 1. The output of the FIS depends upon the type of fault and hence the defuzzified output varies from 1 to 15 (as shown in Table 3).

The testing of the proposed method under various operating conditions, different fault resistance and fault inception angles and correspondingly result obtained shows that the results are satisfactory.

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