Transient Fault Area Location and Fault Classification for Distribution Systems Based on Wavelet Transform and Adaptive Neuro-Fuzzy Inference System (ANFIS)

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Abstract. *A novel method to locate the zone of transient faults and to classify the fault type in Power Distribution Systems using wavelet transforms and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) has been developed. It draws on advanced techniques of signal processing based on wavelet transforms, using data sampled from the main feeder current to extract important characteristics and dynamic features of the fault signal. In this method, algorithms designed for fault detection and classification based on features extracted from wavelet transforms were implemented. One of four different algorithms based on ANFIS, according to the type of fault, was then used to locate the fault zone. Studies and simulations in an EMTP-RV environment for the 25 kV power distribution system of Canada were carried out by considering ten types of faults with different fault inception, fault resistance and fault locations. The simulation results showed high accuracy in classifying the type of fault and determining the fault area, so that the maximum observed error was less than 2 %.*

Keywords

Adaptive Neuro-Fuzzy Inference System (ANFIS), electrical distribution systems, fault classification, fault detection, fault location, wavelet transforms.

1. Introduction

Fault location is a key issue in the protection of power systems and accurate and swift fault location processes reduce expected energy that will not be supplied, increase system efficiency and promote customer satisfaction with the power distribution system. Implementation of fault location algorithms in power systems needs to consider both transmission and distribution networks. Prolonged fault correction processes in power systems may cause irreparable damage, and consequently, rapid fault detection and correction in these systems is of the utmost importance. Measurements of voltage, current, power and frequency in transmission lines can be made with high precision, allowing the exact fault location to be determined quickly and timely action taken to resolve the problem. A variety of algorithms has been presented in the literature and a number of them have been applied to practical networks [1], [2] and [3].

In distribution networks, each feeder of a distribution substation covers a large area and, unlike transmission networks, it is not a straight line but rather a line composed of several laterals. In addition, each feeder includes a variety of distribution transformers. Therefore, fault location in distribution networks is more challenging, costly, and less accurate than for transmission systems. Few studies have explored this issue [4], [5], [6] and [7].

Fault location in a distribution network is faced with the following problems that complicate the process of determining the fault location:

- The wide expansion of distribution network feeders and their laterals.
- Different types of overhead and underground cables, with varying cross-sectional areas and phase configurations, in different parts of the distribution network.
- The presence of distribution transformers in different parts of the distribution network, with varied nominal capacities and loading factors.
- The existence of just one data logger for fault voltage and current at the beginning of the distribution network feeders.

The methods for fault location in power systems are divided into two major categories: impedance and travelling waves [5] and [7]. However, as fault location is more difficult in distribution networks, given problems such as several laterals, fault location in distribution networks is divided into two major parts: (1) locating the fault zone, (2) determining the exact location of fault. First, the faulted zone is exited from the network and then exact fault location is determined. The purpose of this paper is to introduce new methods to determine the area of the fault (faulted zone).

Reference [8] estimated the fault zone using current patterns, and re-closer-fuse coordination. Reference [9] used an algorithm based on a matrix to locate the fault zone. In this method, the arrays were made of binary data (0 and 1) transmitted from Feeder Terminal Units (FTU). Reference [10] proposed a synchronized voltage-based non-iterative method by taking advantage of the substitution theorem. By replacing the faulted line with a suitably adjusted current source injecting the same amount of transmission line current, an equivalent network was established. A two-stage fault location algorithm using Radial Basis Function (RBF) based Support Vector Machine (SVM) and Scaled Conjugate Gradient (SCALCG)-based Artificial Neural Network (ANN) was proposed in [11]. In the first stage, the magnitudes of the fundamental harmonics of the positive sequence voltage and current signals of the faulted phases were input to RBF-based SVM to get an approximate fault area. In the second stage, the SCALCG-based ANN was implemented to indicate the precise fault location using high frequency characteristics. The impedance-based method proposed in [12], locates the fault in a hierarchical manner, in which the faulted zone, faulted line and fault point are located in turn. Reference [13] proposed a multi-objective optimization method using a Non-Dominated Sorting Genetic Algorithm (NSGA) algorithm to determine the location of faults in the distribution system.

When a fault occurs in power systems, fast and accurate fault classification (for post-fault analysis) and restoration of the system to its original state are of the utmost importance. In many fault location methods, information about the type of fault is the basis of fault location, so the correct classification of faults affects the precise detection of the fault zone. Given the importance of fault classification for relay performance, many studies have focused on fault classification problems in the transmission system [14], [15] and [16]. Studies of fault classification in power systems are divided into two groups: (1) designs that utilize steady state electrical components [17], [18] and [19], and (2) designs that utilize transient electrical components [20], [21] and [22]. For example, Ref. [18] used an algorithm based on fuzzy logic to determine the type of fault in radial unbalanced systems. Reference [20] used a new approach, based on wavelet transforms, to identify and classify the type of fault by comparing the waveforms. Reference [22] developed a new method to classify the type of fault, using Adaptive Neuro-Fuzzy Inference Systems (ANFIS). This method was based on applying wavelet transforms to the fault current.

Since most faults occurring in power systems are transient in nature [23], in this paper, we propose a new algorithm to determine the area of transient fault in distribution networks using ANFIS. Based on features extracted from the main feeder current, novel algorithms for detecting and classifying different types of faults are presented. This information is then used to detect the fault zone.

Four algorithms were designed to detect the fault zone, one for each type of fault (single-phase-to-ground, double-phase-to-ground, phase-to-phase, three-phase/three-phase-to-ground). The fault zone was then determined using trained ANFIS networks.

EMTP-RV is used for simulations. Simulations were carried out in three steps: (1) identification of the fault, (2) classification of the fault type, and (3) location of the faulted zone. This method is less complex than previously reported methods as there are no long and complex calculations involved, and the faulted zone is determined promptly (approximately 4 cycles). This method also has higher accuracy, when compared with other studies [22] and [24]. A further advantage of this method is that identification of the fault and classification of the fault type are completely independent of line and fault parameters.

2. Wavelet Transform Analysis

The inputs for the designed algorithms were features extracted from the main feeder current, which were derived from wavelet transforms. Wavelet transforms can be considered as an extension of Fourier transforms, but instead of working on one scale (frequency or time), they work on multiple scales. This multi-scale feature of wavelet transforms leads to the decomposition of a signal into several scales, with each scale representing a particular feature of the signal under study [25]. Wavelet transforms divide the signal into different levels, each level containing frequency-time information for the signal. In this study, features of the profile of transients are taken for the 2000–4000 Hz range. The process for Multi-Resolution Analysis (MRA) of the input signal is shown in Fig. 1.

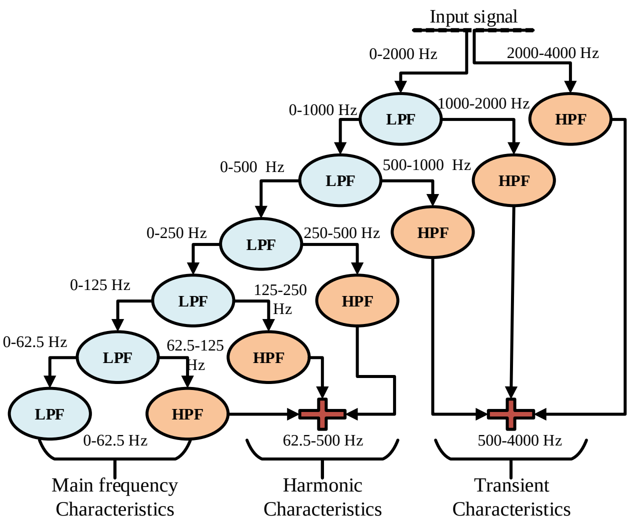

Fig. 1: Frequency division multi-resolution levels up to 6.

3. Adaptive Neuro-Fuzzy Inference Systems (ANFIS)

ANFIS is one of the models of neuro-fuzzy systems. Neural networks and fuzzy systems are both independent systems. Increasing training processes, increasing membership functions, and independent fuzzy rules are factors in complexizing problem solving. This led to the development of the ANFIS method, which combines the benefits of both neural networks and fuzzy logic. ANFIS aims to eliminate the disadvantages of each of these systems while retaining their complementary benefits [26]. Fuzzy logic in this system is used as a contributor to the training algorithm and can adjust the parameters of the fuzzy system.

4. Estimating Fault Time Algorithm

Firstly, the main feeder currents in each cycle are received and their essential characteristics are obtained from their wavelet transforms. Based on a waveform analysis of the fault signal at different times, it was found that in all cases, the waveform obtained from the wavelet transform of the main feeder current, at the time of transient fault, possessed the highest jump. By comparing momentary variations in a sample with the previous sample in each cycle, the maximum variation of the wavelet transform can be detected. If there were no fault in the selected cycle, the sum of variations would be equal to zero. If a fault takes place, the time of maximum change is considered as the time of fault occurrence. For example, wavelet transform of phase-A during fault occurrence in node 6 of the 25 kV power distribution system of Canada [27] with a resistance of 40 ohms and a fault inception of 10 degrees, is shown in Fig. 2. Figure 3 shows changes from moment to moment. It can be seen that the moment with the highest change in value was considered as the fault occurrence time.

As shown in the flowchart in Fig. 4, to avoid interference in detecting the time of the transient fault with enter or exit loads, after determining the start time of disturbance in the wavelet transform current signal, the duration of the disturbance is calculated using a transient detection flag. If this time is less than 3 cycles, the disturbance in the current signal is considered as a transient fault and the fault time is estimated. Using the algorithm in Fig. 4, the fault detection time and fault occurrence were 4 microseconds, thereby indicating high precision in a cycle of 16.6 milliseconds.

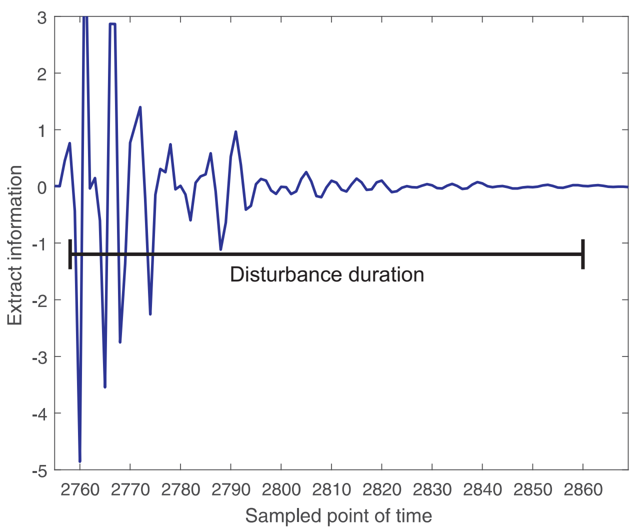

Fig. 2: Current wavelet transform of phase A (During fault).

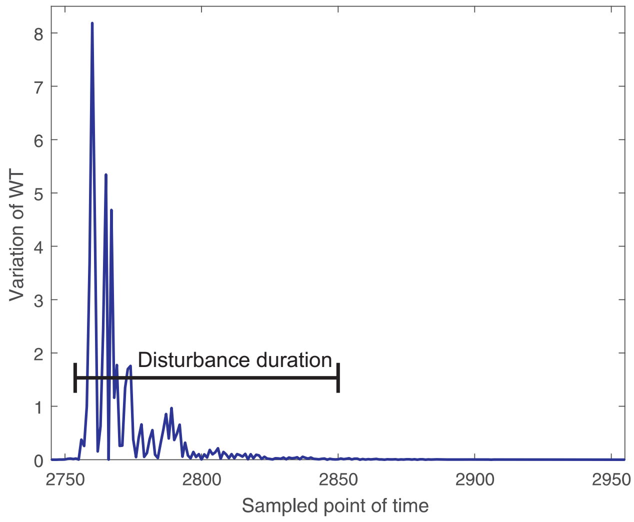

Fig. 3: Instantaneous changes of the current wavelet transform of phase A.

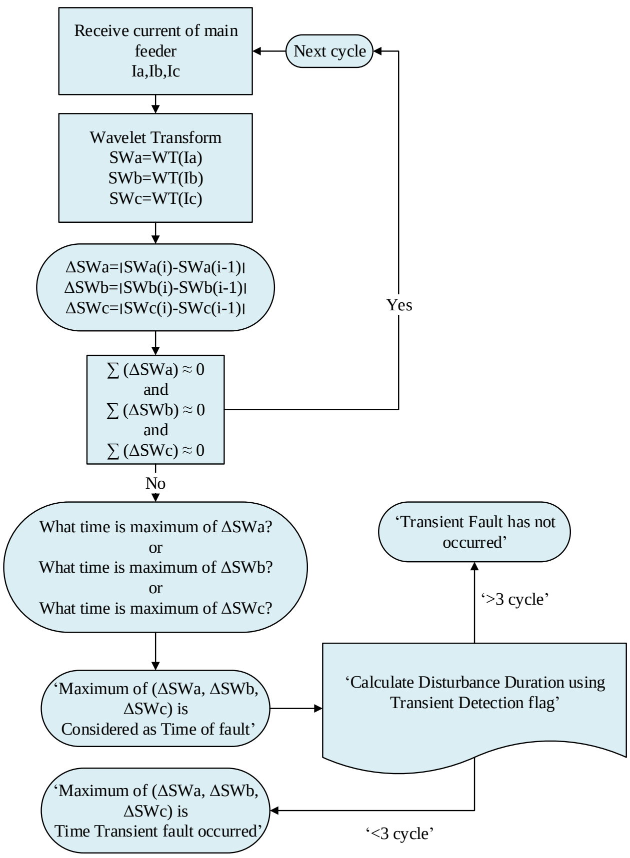

Fig. 4: Flowchart of the algorithm for estimating fault time (i is the number of samples taken in one cycle).

5. Fault Classification Algorithm

In most fault-locating algorithms, fault classification is one of the most important parts of the process. In this study, a new algorithm to classify the type of fault based on features extracted from the main feeder current is presented. Analysis of the wavelet of the fault signals revealed that signals extracted from wavelet transforms displayed specific behavior for each type of fault.

For example, in the case of phase-to-phase faults, the sum of the wavelet transforms of the phases involved from the main feeder current was almost equal to zero (Fig. 5), while in the case of single-phase-to-ground faults, wavelet transforms of the two phases without faults were almost equal. Figure 6 shows the wavelet transforms of the three-phases when a C-phase-to-ground fault took place. It can be seen that the Phase-C wavelet transform with the fault is distinct, but wavelet transforms for the other two phases display similar behavior.

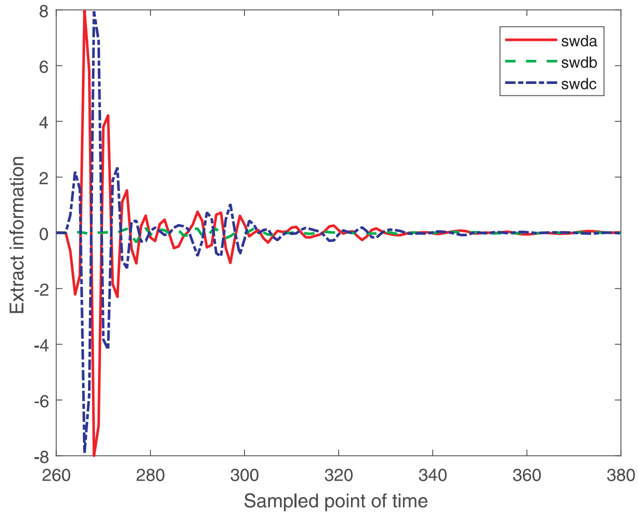

Fig. 5: Wavelet transform of three-phase current during AC phase-to-phase fault (during fault).

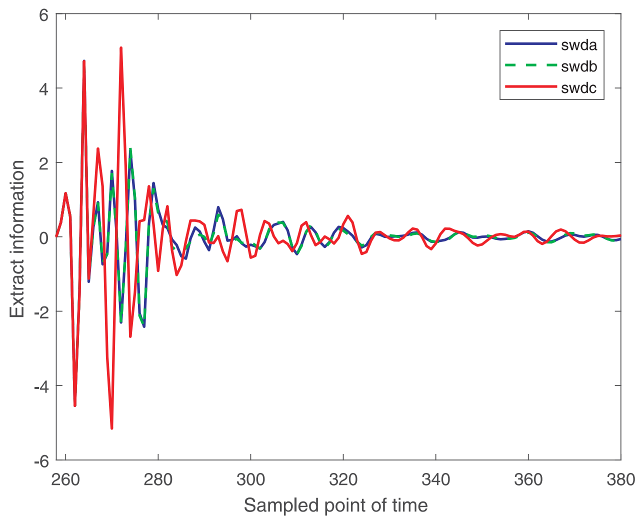

Fig. 6: Wavelet transform of three-phase current during Cg single-phase-to-ground fault (during fault).

If the above conditions are not established to determine the type of faults, the absolute value of the difference between the maximum current peak of each phase during and before the fault is computed. Then, magnitudes obtained from each phase are compared with each other. If values obtained for one phase are negligible compared to other phases, the phase is considered to be without fault and the number of faulty phases can be estimated (Fig. 7, Fig. 8, Fig. 9 and Fig. 10).

For example, in Fig. 8 a double-phase-to-ground fault occurred in the AB phases. It can be seen that the difference in current peak in phase C before and during the fault is insignificant, but in phases A and B, there are significant differences (approximately 2 times greater than before the fault for phase A and approximately 6 times greater for phase B). Similarly, for three-phase-to-ground faults, shown in Fig. 7, the difference between current peak before and during the fault for all three phases is high. For phase-to-ground faults, only the difference between the current peak before and during the fault in the faulty phase is high (Fig. 10). Similarly, for phase-to-phase faults (Fig. 9) given the difference between the current peak before and during the fault, the same conclusion can be reached for each phase. Figure 11 shows a flowchart of the fault classification algorithm. This algorithm is independent of the resistance, location and fault inception.

The algorithm for the classification of fault type is initially implemented with respect to the detection algorithm, provided that a fault has taken place in the network.

In the first step, the wavelet transforms of the three-phases of the main feeder current are summed up pairwise and provided that the estimated sum of at least one of the wavelet transforms is zero it is considered

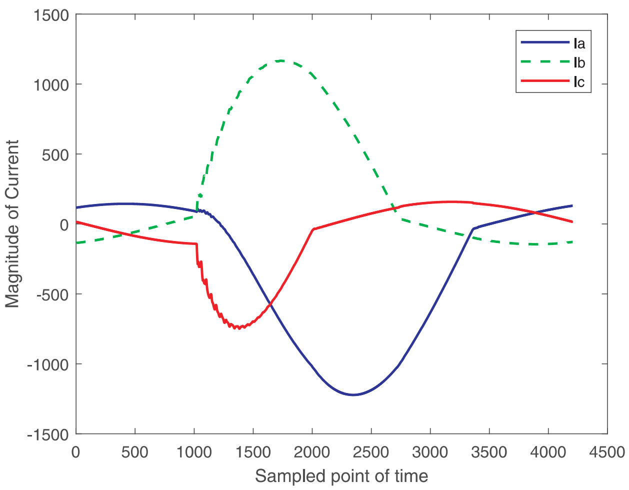

Fig. 7: Waveform of three-phase current during ABCg three-phase-to-ground fault (during fault).

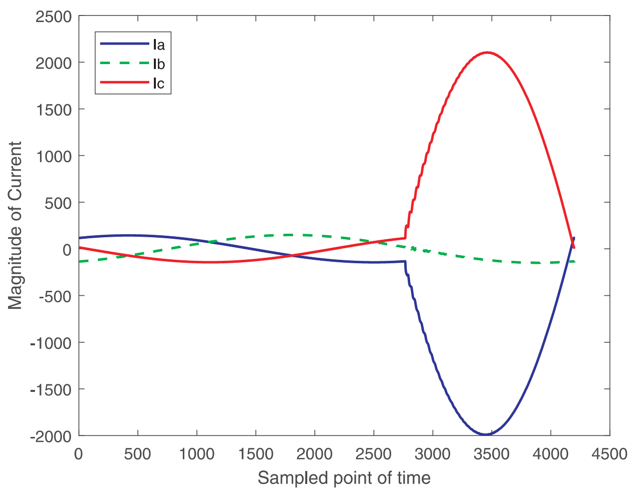

Fig. 9: Waveform of three-phase current during AC phase-phase fault (during fault).

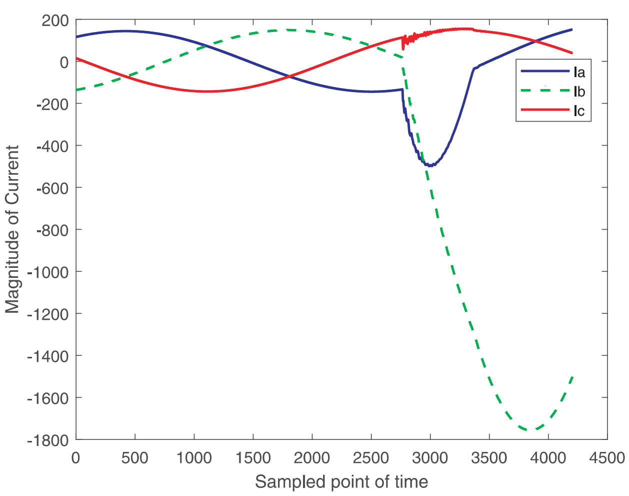

Fig. 8: Waveform of three-phase current during ABg double-phase-to-ground fault (during fault).

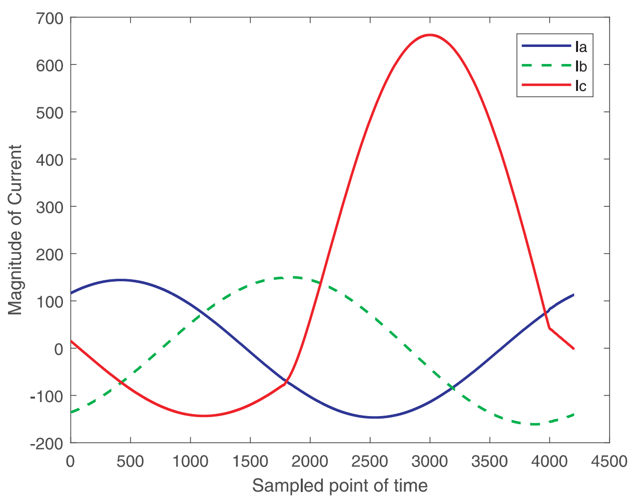

Fig. 10: Waveform of three-phase current during Cg single-phase-to-ground fault (during fault).

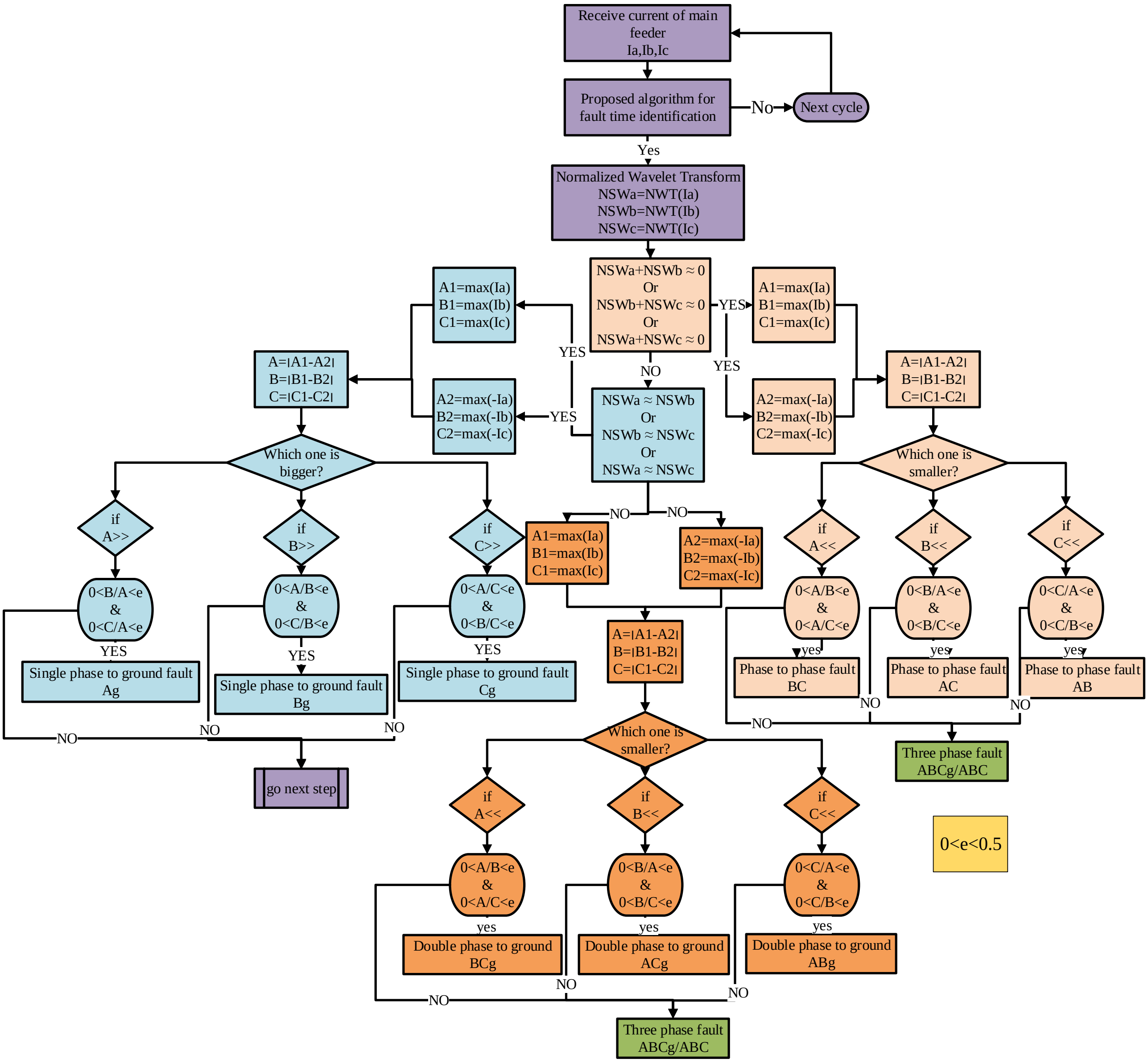

Fig. 11: Flowchart of the fault classification algorithm.

as a phase-to-phase fault. In the next step, to ensure that the fault is phase to phase, the current peak difference before and during the fault is checked for each phase. If the difference between the current peak before and during the fault is high for all three phases, the fault type is determined as three-phase. If the sum of wavelet transforms of paired phases is not approximately equal to zero, it proceeds to the next step. At this point, if the wavelet transform of one phase is similar to another phase, a single-phase-to-ground fault is considered. Then, to ensure that the fault is single-phase, the difference between the current peak before and during the fault is calculated. If the difference between the current peak before and during the fault is significant in more than one phase a single-phase-to-ground is rejected and the next step is considered.

The flowchart in Fig. 11 shows that in classifying phase-phase-to-ground and three-phase fault types only the absolute value of the difference between the maximum current peak of each phase during and before the fault is used.

6. Fault Area Location Algorithm

To avoid the failure of all lines during a fault and to continue power supply to the systems, distributed systems were divided into separate regions [28]. The division of regions in the distribution system was based on system topology, the presence of protective devices,

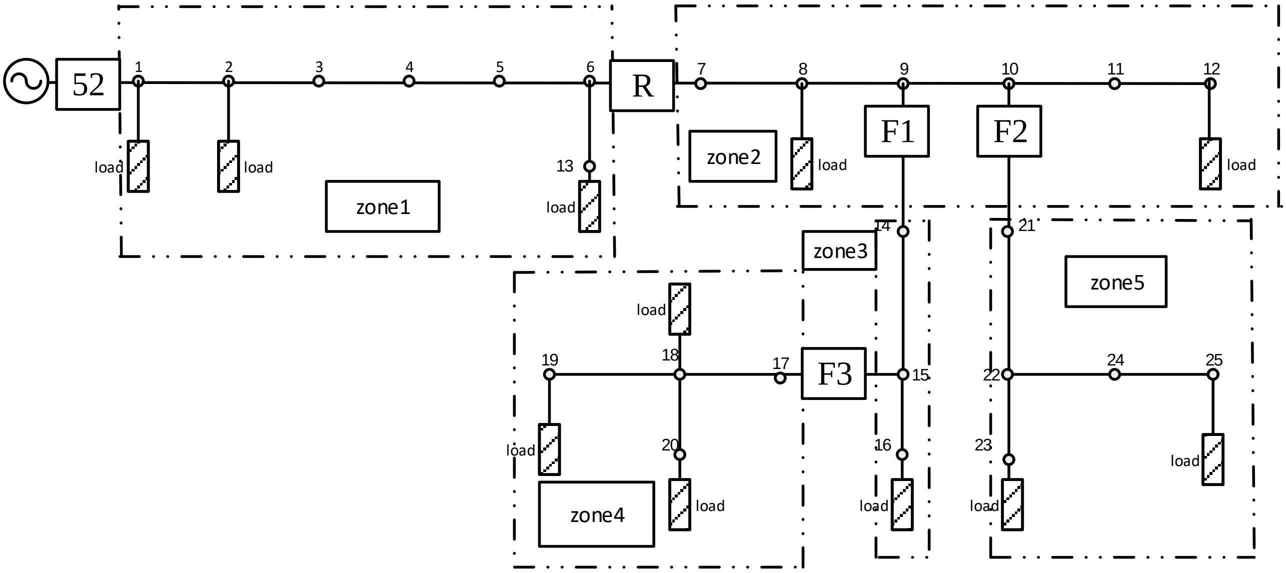

Fig. 12: Diagram of the 25 kV power distribution system of Canada.

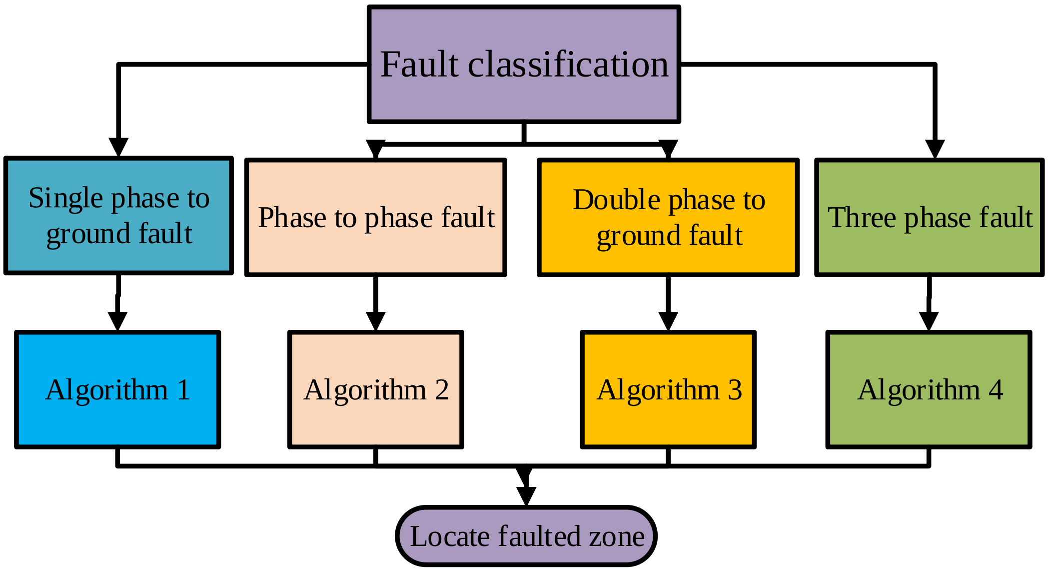

Fig. 13: Flowchart to locate the faulty zone.

the length of feeders, etc. [29]. As an example, the 25 kV power distribution system of Canada [27] was studied as a practical system (Fig. 12). This system was divided into five regions with respect to protective devices, and in case of a fault in each region, the faulty zone was detected and only the specified area was disconnected from the circuit.

After completing the process of estimating fault time and classification of fault type, the fault zone location was determined using the ANFIS system. To locate the fault zone, data from the three-phase wavelet transform current was directed to the appropriate algorithm, one for each type of fault (Fig. 13). In this algorithm, to reduce data interferences and diminish errors in the location of fault zone using the ANFIS system, data were analysed in smaller batches. According to the algorithm flowchart shown in Fig. 14, after determining the type of fault, the trained inference system for this fault type was used.

7. Evaluation of the Performance of the Proposed Algorithms

7.1. Estimating the Fault Time

To evaluate the performance of the algorithm in estimating fault time, it was implemented for ten types of

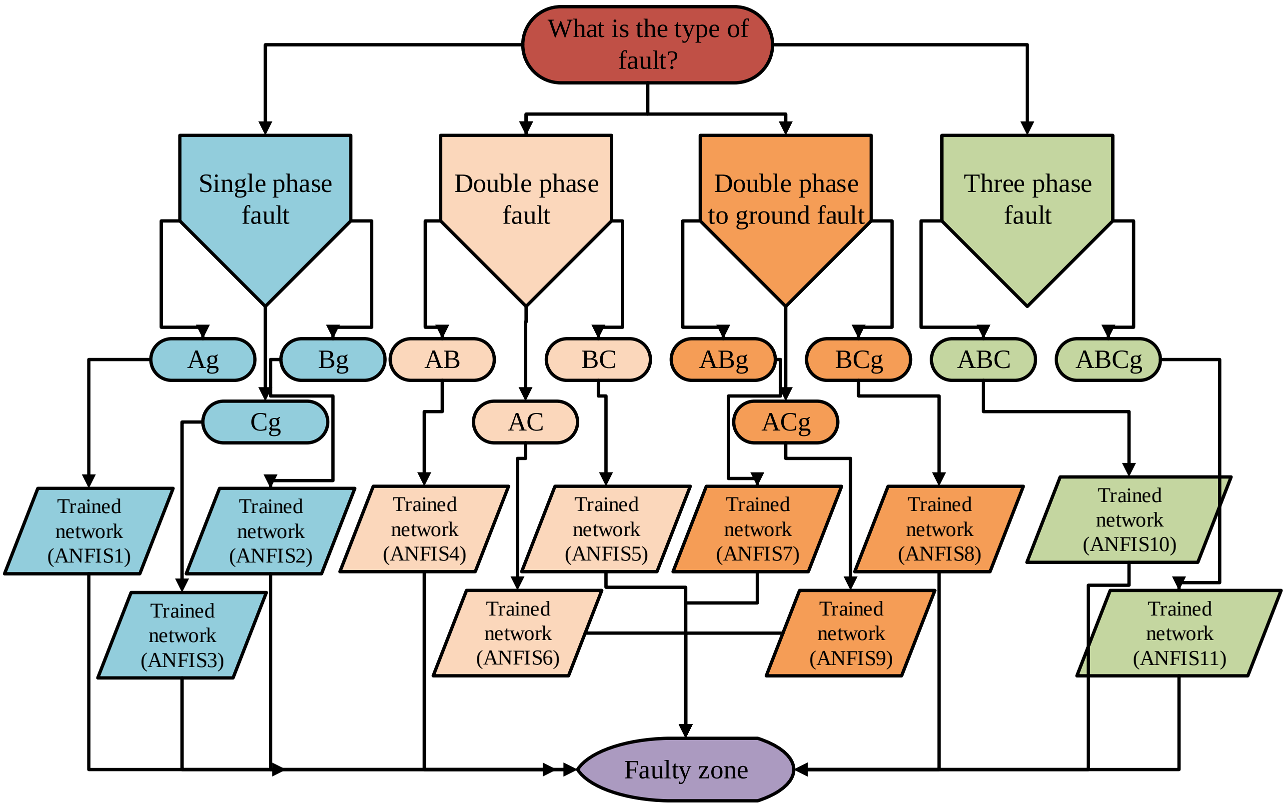

Fig. 14: Flowchart of the fault area location algorithm.

faults with varied starting angles at 20 random locations in the 25 kV power distribution system of Canada [27]. The results are shown in Tab. 1. The accuracy of the algorithm was computed using Eq. (1):

$$\text{percentage accuracy} = \frac{\text{real time of fault} - \text{estimated fault time}}{\text{duration of one cycle}} \cdot 100. \quad (1)$$

In Tab. 1, it can be seen that the largest error in estimating the fault time was 1 %, which indicates a high accuracy for the algorithm.

7.2. Evaluating the Performance of the Fault-Type Classification Algorithm

To evaluate the performance of the fault-type classification algorithm, the algorithm was run for ten types of fault in one location in the 25 kV power distribution system of Canada (node 6, fault resistance 40 ohms, fault inception 8 degrees) [27]. The results are presented in Tab. 2. For example, in the first row, a single-phase-to-ground fault Ag took place. As discussed in Sec. 4. , in single-phase fault mode, the wavelet transforms of the fault-free phases are almost identical (SWb = SWc) and by comparing the difference between the peak current of the phase, both during and before the fault, with the other phases, it can be determined whether a fault has occurred in phase A $\left(\left|\max\left(\left|i_a^{df}\right|\right) - \max\left(\left|i_a^{bf}\right|\right)\right|\right)$.

Similarly, for the fourth row where an AB phase-to-phase fault took place, by comparing the wavelet transform of the current, it was observed that the wavelet transforms of the A and B phases were symmetrical (SWa + SWb = 0). Also, by comparing the difference of the current peaks, both before and during the fault, with the other phases, it could be determined whether a fault had taken place in phases A or B $\left(\left|\max\left(\left|i_a^{df}\right|\right)\right| - \left|\max\left(\left|i_a^{bf}\right|\right)\right|\right.$ and $\left.\left|\max\left(\left|i_b^{df}\right|\right)\right| - \left|\max\left(\left|i_b^{bf}\right|\right)\right|\right)$. It should be noted that the proposed method had 100 % accuracy in classifying the fault type, this was not observed in previous studies [22].

7.3. Evaluating the Fault Area Location Algorithm

As mentioned previously, the main purpose of the presented paper is to determine the fault region in the distribution system, and the precise location of the fault is not considered. On the other hand, to obtain sufficient data for training the ANFIS network, different types of faults in varying nodes and under different fault resistance, fault inception and fault types (to 1000 epochs)

Tab. 1: Evaluation of the performance of the estimating fault time algorithm.

Type of fault	Fault location (node)	Fault impedance Ω	Real time of fault (ms)	Estimated fault time (ms)	Error of estimated fault time
ABg	1	10	15	14.8293	1 %
BCg	6	20	11	10.9283	0.4 %
Bg	12	40	7	6.9601	0.2 %
Ag	8	80	4	4.0156	0.09 %
ACg	9	10	1	1.0984	0.5 %
BCg	11	20	15	14.9519	0.2 %
Bg	13	40	11	10.9323	0.4 %
Bg	14	80	7	7.0155	0.09 %
Bg	15	10	4	4.0354	0.2 %
Bg	16	20	1	1.075	0.4 %
Bg	17	40	15	14.9804	0.1 %
Cg	18	80	11	10.9876	0.07 %
Cg	19	10	7	6.9325	0.4 %
ABC	6	0	11	10.9402	0.3 %
AC	8	20	11	10.9679	0.1 %
ABg	11	80	4	4.0275	0.1 %
Bg	14	80	11	10.9679	0.1 %
Bg	16	40	7	7.0036	0.02 %
Cg	21	20	4	4.0354	0.2 %
Cg	18	20	11	10.9718	0.01 %

Tab. 2: Evaluation of the performance of the estimating fault time algorithm.

Type of fault	SWa	SWb	SWc	max $\left(i_a^{bf}\right)$	max $\left(i_b^{bf}\right)$	max $\left(i_c^{bf}\right)$	max $\left(i_a^{df}\right)$	max $\left(i_b^{df}\right)$	max $\left(i_c^{df}\right)$
Ag	5.703	-3.24	-3.24	144.1712	149.0179	152.1604	943.6845	146.4857	143.3865
Bg	4.556	-2.566	-2.566	180.7221	149.0179	144.0064	171.35	7109.5	143.3865
Cg	13.78	1.758	1.758	144.1712	149.0179	143.3865	149.0797	197.2185	4566.4
AB	0.6724	-0.6752	0.0009	144.1714	149.0179	143.3915	6400.5	6401.8	143.3865
BC	0.0006	-7.908	7.906	144.1712	149.0179	143.3865	153.959	7395.7	7287.2
AC	-3.794	0.1803	3.807	144.1712	149.0179	143.3865	2334.2	149.029	2446.8
ABg	-1.497	-0.5625	4.46	182.5789	149.0179	159.6409	885.6958	5454.3	143.3865
BCg	1.714	-8.864	6.0343	144.1712	149.0179	143.3865	144.174	6700.6	3773
ACg	7.531	2.004	-5.567	144.1712	149.0179	143.3865	636.7509	156.3637	3719
ABCg	3.241	-0.629	-2.207	144.1712	149.0179	143.3865	949.447	6627.6	3902.8

were simulated and the collected data used for training the ANFIS network (Tab. 3).

The data necessary for testing the trained network are shown in Tab. 4. Faults identified outside the fault zone by the ANFIS network were considered as incorrect. The accuracy of the proposed method is calculated from Eq. (2):

$$\text{percentage error} = \frac{\text{incorrect answer}}{\text{total of answer}} \cdot 100. \quad (2)$$

Tab. 3: Training data.

Faulty node	1,9,12,13,16,19,20,23,25
Fault resistance	0,10,20,40,80
Fault inception	11,43,75,118,161
Total of data	1125

Tab. 4: Testing data.

Faulty node	6,10,15,18,22
Fault resistance	5,15,30,50,70
Fault inception	8,54,96,108,144
Total of data	575

Table 5 shows the data used for each fault, based on the fault phase as well as the share of each one in the process of training and testing the ANFIS network. In Tab. 6, the evaluation of the fault location algorithm and the accuracy of the algorithm for each fault phase based on the number of data is shown.

Tab. 5: Data used to train and test the fault area location algorithm.

Type of fault	Faulty phase			Process	
Single phase to ground	Ag	Bg	Cg	Train	Test
	225	425	225	275	150
Double phase to ground	ABg	ACg	BCg	Train	Test
	150	150	150	300	150
Double phase	AB	AC	BC	Train	Test
	150	150	150	300	150
Three phase	ABCg/ABC			Train	Test
	150			100	50

The proposed method for fault identification was assessed for 10 types of faults in different locations and under different conditions and compared with the method developed in [24]. The results are shown in Tab. 7.

Tab. 6: Evaluation of the fault area location algorithm.

Type of fault	**Faulty phase**			**Process**
Single phase to ground	Ag	Bg	Cg	Test
	50/50	100/95	75/75	275
Accuracy	100 %	95 %	100 %	97.7 %
Double phase to ground	ABg	ACg	BCg	Test
	50/50	50/50	50/49	150
Accuracy	100 %	100 %	98 %	99.3 %
Double phase	AB	AC	BC	Test
	50/50	50/50	50/50	150
Accuracy	100 %	100 %	100 %	100 %
Three phase	ABCg/ABC			Test
	50/50			50
Accuracy	100 %			100 %

Tab. 7: Comparison between the proposed method and the method of [24].

Type of fault	**Percentage of Accuracy**	
	In this paper	**In [24]**
Line to ground	95.55 %	98.33 %
Line to line	100 %	100 %
Double line to ground	78.87 %	99.33 %
Three phase	100 %	100 %

8. Conclusion

In this paper, novel methods for the detection of fault occurrence, fault classification and fault location are proposed. The algorithms presented in terms of chronological order depend on each other. The first two of these methods involves algorithms that were designed using features extracted from the wavelet transform. The results from these algorithms showed minimum errors in performance. Four algorithms for fault location were designed for different types of fault. The distribution network under study was divided into five zones based on protective objectives, so that in the case of fault detection in each zone, only the faulty zone was disconnected from the circuit. Results from the fault location process showed that this method had high accuracy. This was due to the high performance of the algorithms that identify fault inception and the fault type and prevented interference of data in the fault location algorithm, so that the maximum error in fault location for a single-phase-to-ground fault was 2 %. Although the proposed algorithm is capable of detecting load entry/exit and distributed generation systems, accurate performance in the presence of distributed generation sources requires the development of the proposed algorithms, which is of the authors' goals in future research.

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