Fault Classification in Jointed Overhead-Underground Distribution Lines. A review paper.

Dorothy Wanjiku Gicheru Edwell Mharakurwa and Waweru Njeri

Department of Electrical and Electronics Engineering, School of Engineering, Dedan Kimathi University of Technology, Private Bag, Nyeri, 7381, Kenya, E-mail: dorothy.gicheru@dkut.ac.ke

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Abstract: With the current economic expansion, power demand is continually growing. Distribution lines making up most of the power system are crucial for distributing power from the power plant to the consumer. Power distribution can be done via overhead lines or underground cables, but there are instances where a combination of both is utilized. These lines are susceptible to faults like any other electrical system, primarily brought on by moisture in the paper insulation, cable brittleness, or flaws in splices or other accessories. Due to the low power distribution efficiency caused by these faults, there is a significant annual power loss. The secret to improving the dependability and ideal performance of the system is discovering and developing new techniques to pinpoint the type of fault. This paper examines numerous methods for classifying faults in a jointed overhead-underground distribution line.

Keywords: Underground cable, overhead line, neural network, faults, and discrete wavelet transform.

1. Introduction

Overhead and underground cables are used to transmit or distribute electric power[1], but underground cables are infrequently used for electricity distribution due to the following factors. First, since power is typically transported over great distances to load centers, installing underground distribution will be exceedingly expensive. The upfront installation costs for an underground system are about twice as high as those for an overhead system[2].

Power distribution via overhead distribution wires is becoming the norm due to the constant rise in voltage level brought on by an increase in power demand. The fact that the overhead distribution system is more adaptable than the underground system is another benefit of the latter. For load expansion in an overhead system, more conductors can be placed alongside current ones. Such new conductors will be installed in new channels in underground distribution systems as needed for load expansion. Although defects in underground systems are extremely unlikely to happen, if they do, they are always far more challenging to find and more costly to fix than failures in overhead systems[3].

The underground system has several advantages over the overhead system, including safety, maintenance costs that are much lower, no interference with communication circuits, and no interruption of service due to lightning, thunderstorms, or objects falling on the wires. Additionally, the underground cable can traverse urban areas, protected landscapes, rivers, and transportation hubs. The natural advantage of the underground cable causes it to be designated for areas of particular environmental importance, such as; crossing an area that is too wide for an overhead line, such as a lake. Underground cables are also used to operate in urban/semi-urban areas unrecognized by society and exceptionally environmentally constricted areas for specific ecological, aesthetic, or historical reasons (Kulkarni et al., 2014; Rasoul jaafari Mousavi, 2007).

No dispute that using underground cables helps the environment and relieves public pressure, but due to their high initial capital and life cycle costs, they can only be used in distribution networks. Therefore, a mixed distribution line with primarily overhead but underground sections offers a financially feasible and environmentally acceptable alternative

and aids in avoiding planning restrictions and public objections due to visual intrusion. However, it creates issues for the effective functioning of control and protection devices, particularly for auto-reclosure intended to recover a line after a temporary malfunction[6]. The distribution system's reliability increases and operational expenses are decreased with quick power flow restoration. On the other hand, a fault on an underground cable is more harmful since it damages the cable because the fault current increases the cable's internal temperature.

Additionally, specific pipe-type cables utilize oil as an insulator. If they have a problem, the oil could leak into the ground in enormous quantities, polluting the environment. Determining the sort of problem that has occurred is crucial for these reasons.

Like any electrical device, overhead and underground lines are prone to faults[7]. Power line faults are abnormalities that cause current to divert from its intended course, resulting in an anomalous state that weakens the insulation between conductors. A series of faults in an underground or overhead cable can cause lead to crystallize and the cable to age more quickly as a result of moisture infiltration or mechanical damage.

Additionally, cable faulting can come from a cut without destroying the electrical insulation, overloading, deterioration, and subjection to mechanical, chemical, or electrical conditions.

The two main types of faults are open and short circuit faults [8], as shown in fig.1.

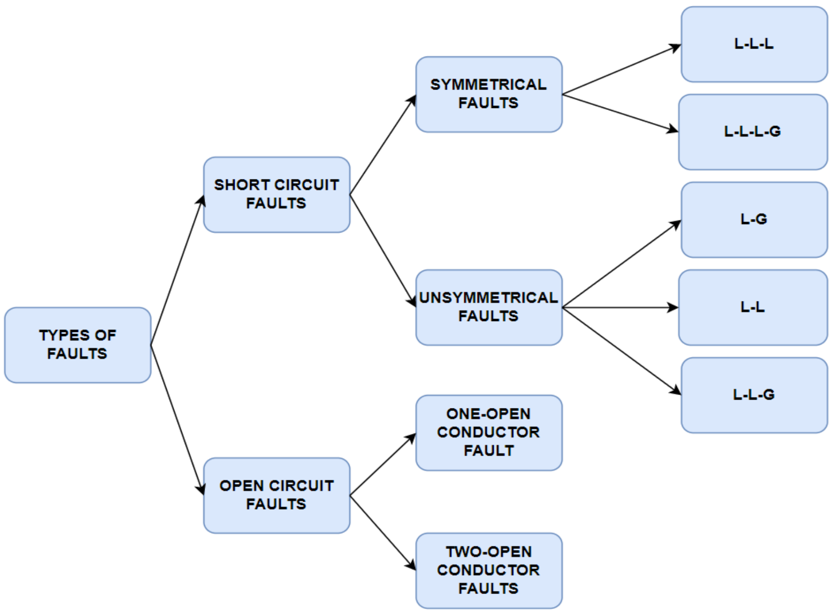

Figure 1 Types of Faults

If these faults are not identified, categorized, and accurately fixed promptly, they result in considerable losses for both the customer and the supplier. Therefore, precise fault categorization is essential for reducing power system operating costs, restoring service as soon as possible, and increasing the reliability of the power system. The emergence of general topologies, such as overhead lines attached to underground cables, makes fault detection and categorization more challenging[9].

In order to prevent catastrophic damages, the protection mechanism must quickly identify the fault and classify and pinpoint its location. There have been numerous approaches developed, each with unique benefits and drawbacks. Therefore, consumers have a difficult task in choosing a fault categorization approach. Therefore, reviewing all the effective and efficient fault categorization techniques suggested is necessary. Several fault categorization techniques are discussed in the literature and how they are carried out. The fault classification techniques have also been discussed in this review article based on the techniques and simulation tools employed in the complementary approach. This review article provides an overview of the existing fault categorization techniques.

2. Fault classification methods survey

In a power system, overhead power lines are the easiest to examine because the fault is typically self-evident, such as when a tree falls across the line or when a utility shaft breaks and the wires are left on the ground. The most crucial components for protecting an overhead line are accuracy in fault categorization and fault recognition[3]. Growing transmission and distribution infrastructure is needed in conjunction with new generating plants to provide the rapid increase required. It is crucial to resolve transmission failures using fast protection solutions due to the ensuing lower dependability restrictions, and this has sparked new interest in transient-based protection approaches. Traditional and hybrid fault classification approaches are frequently used [10].

With traditional techniques[11], protective relays located at the end of a power line immediately detect a defect and isolate it by opening the circuit breakers connected to it. Distance relays are a quick and accurate approach to finding the source of the problem. They do not, however, provide precise fault localization. Additionally, using relays to identify and categorize faults is challenging. The same goes for impedance and traveling wave methods; for fault categorization, their accuracies are low, necessitating alternative methods to circumvent this limitation.

[12]Hybrid techniques involve combining the traditional methods with the Artificial Intelligence method; they are better than traditional methods because they reduce computational work, improve accuracy, and are fast. Below is a brief theoretical review of some of the methods.

2.1 Wavelet method

In the wavelet transform, the scales are adjusted per the frequency. The wavelet transform involves calculating numerous stages, which generates a significant amount of data and requires extensive processing. In order to maximize efficiency, scaling and shifting based on the power of two can be used. The discrete wavelet transformation can produce this analysis[13]. Equation 1 can express the DWT of a signal F(t).

$$\mathrm{DWT}(t,m,n) = \frac{1}{\sqrt{a_o^m}} \sum_{l} F(t)\psi\left(\frac{n - l a_o^m}{a_o^m}\right) \qquad 1$$

The wavelet transform is repeated in the discrete wavelet analyses with a filter bank comprising several high-pass and low-pass filters. The three processes for the wavelet transform of the original signal S are shown in Fig. 2. A signal is divided into an approximation and a detail in the wavelet transform. The approximation is then divided into detail and a second-level approximation, and the procedure is repeated[14].

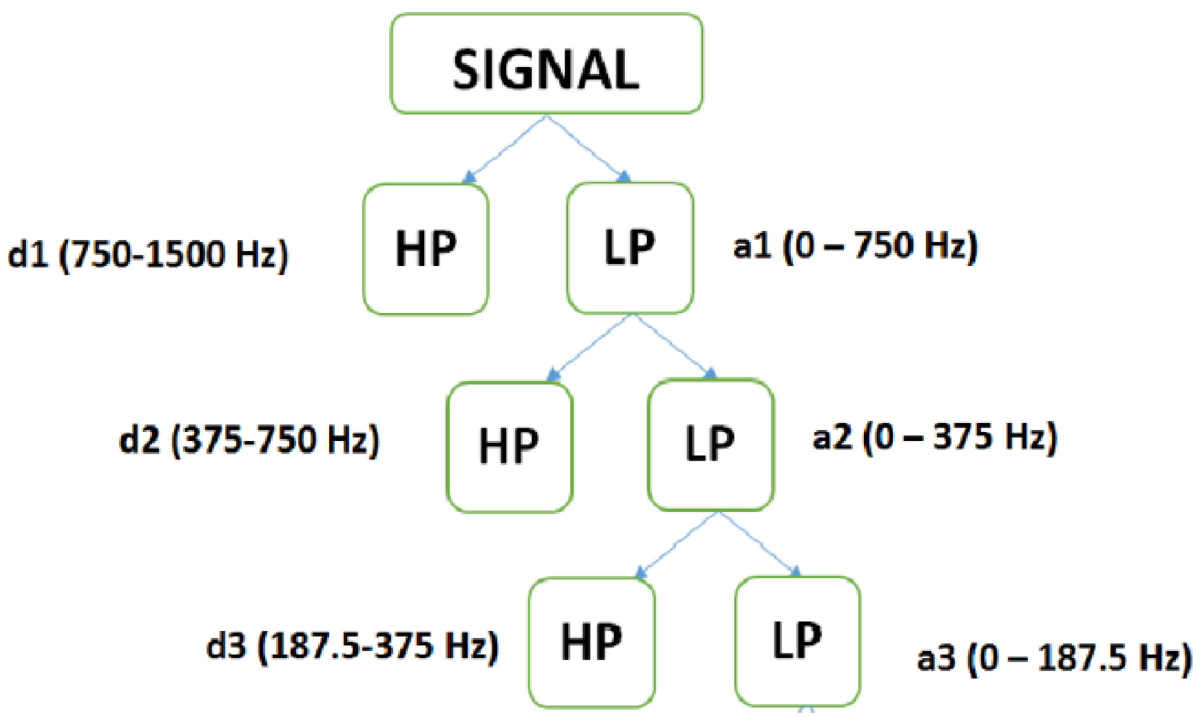

Figure 2 A Signal's Multi-Resolution Analysis in Stages

The detailed component of the signal is the D1 coefficient, which has a high-frequency component, and it is recovered from the modal signal's initial step using the db4 mother wavelet function. The A1 coefficient, which contains the optimal power frequency component, is derived from first-level approximation using a low-pass filter. The same holds for each level's D2, D3, A2, and A3 coefficients[13].

2.2 Artificial Intelligence based method

Artificial Intelligence (AI) is the term used to describe programs or devices that resemble human Intelligence in order to carry out tasks and can incrementally improve themselves based on the data they gather[15]. Listed below are a few artificial intelligence methods.

2.2.1 Artificial Neural Network (ANN)

Artificial Neural Network technology is based on research into the brain and nervous system. Although ANN employs a condensed set of biological brain system ideas, these networks mimic biological neural networks. Particularly, ANN models mimic the electrical activity of the nerve system and brain. Connected to other processing elements are the processing elements themselves. The neurons are often stacked in layers or vectors, with the output from one layer acting as the input for the next layer and possibly others. The technique can be used effectively to comprehend "untrained" or "unknown" cases of the problem once it has been adequately prepared[16]. Figure 3 depicts the basic framework of a simulated neuron model.

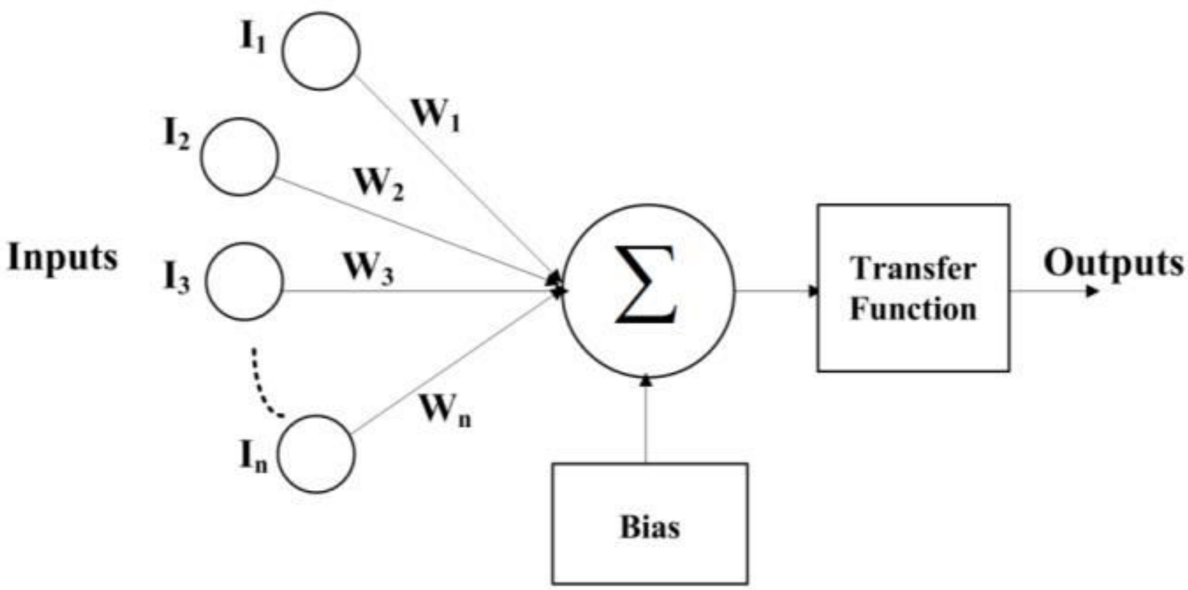

Figure 3 Model of Artificial Neuron

2.2.2 FUZZY LOGIC

Fuzzy logic uses linguistic concepts to control the amicable relationship between output and input variables[17]. As a result, the fuzzy logic approach makes managing and controlling various problems easier, mainly when the numerical model is ambiguous or difficult to resolve. Figure 4 depicts the general process used in a fuzzy system methodology.

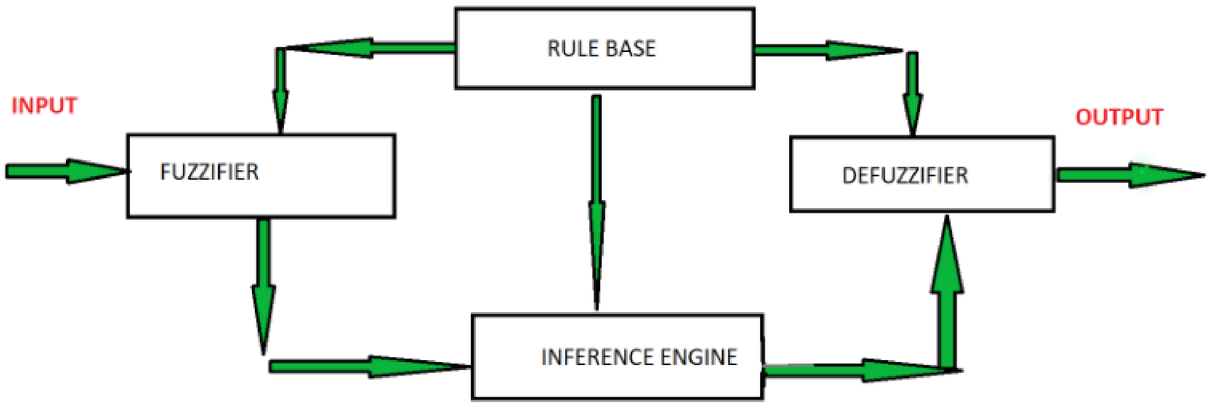

Figure 4 Fuzzy System Model

Based on linguistic data, fuzzification converts inputs, such as crisp numbers, into fuzzy sets. The inference engine gets to decide the matching degree of the current fuzzy input concerning each rule and decides which rules will be fired according to the input field. Defuzzification is used to convert the fuzzy sets obtained into crisp numbers. The rule base includes the rules, and the experts can achieve the IF-THEN development to govern the decision-making system. Numerous defuzzification techniques exist, and the most effective one is combined with a particular expert system to minimize the error[18].

2.2.3 ANFIS

A neuro-fuzzy system model is called an ANFIS. Both fuzzy systems and neural networks are separate systems. The complexity of the issue solution is influenced by rising training processes, expanding membership function parameters, and independent fuzzy rules. As a result, the ANFIS approach was created, which combines the advantages of neural networks with fuzzy logic. ANFIS aims to maintain the complementary advantages of all of these systems while eradicating their drawbacks. This system uses fuzzy logic to help with the training method and to change the fuzzy system's parameters[19].

3. Related Work

[20]A combination of traveling waves and impedance is used to locate faults. However, before doing so, it determines if the fault is grounded or ungrounded by comparing the size of the grounding-type wavelet coefficients at the measuring end. When level 1 detailed coefficients are used, the zero-sequence current estimated using the available information at the line's measuring ends is used to identify the fault type quickly. The fault is grounded if there is zero-sequence current; otherwise, it is ungrounded. [20] does not consider the types of faults; the classification is basically whether a fault is grounded.

To classify fault types, identify faulty sections, and pinpoint the specific location of faults, [21]uses ten Adaptive Network-Based Fuzzy Inference System networks. The fundamental component of phase and zero sequences currents are applied as four inputs to an ANFIS in the first portion to identify the fault type. If the fault is on an overhead line or an underground cable, it is detected using a different ANFIS network. This method's benefit is its ability to categorize different types of defects.

In order to extract significant features and come to coherent conclusions about fault location, [15]uses wavelet transform in conjunction with the fuzzy inference system (FIS) and the adaptive neuro-fuzzy inference system (ANFIS), which incorporates expert evaluation. According to the simulation results, fault inception angle, impedance, and distance have no impact on the classification or localization techniques. This article's most important contribution is that the suggested ANFIS approach outperforms FIS in locating power transmission faults and can thus be utilized as a valuable tool for digitalized relaying applications.

[22] Offers an approach for locating faults in power transmission systems that combines underground cables and overhead lines with single-ended and hybrid traveling wave technology. In the proposed hybrid method, the fault region is identified using support vector machines (SVM), and the discrete

wavelet transformation (DWT) is employed to obtain transient information from recorded voltages. The classifier's input is the post-fault voltages' normalized wavelet energies. Bewley diagrams analyze the traveling wave pattern in the underground cable and overhead line to detect the fault. This method's drawback is that it only classifies faults based on whether they are in the overhead/underground segment, not on their type.

For power transmission networks, [23]offers a single-ended traveling wave-based fault location approach. The traveling wave patterns are identified using Bewley diagrams. The suggested method extracts the transient data from the collected voltage signals using Discrete Wavelet Transform (DWT). The energy of the signals is derived from the squares of the discrete wavelet coefficients (WTC2) to determine the faulted portion, underground line, or overhead line and then locate the fault.

[24] Suggests an algorithm anticipate faults' location and classify fault types with a high degree of accuracy at a low cost. Impedance measurement information from one end of the transmission line is needed for this algorithm to obtain positive sequence impedance; modal decomposition is employed. A discrete wavelet transform is used to deconstruct the defect signal. Statistical sampling provides a standard for the deconstructed signal's fault features that will be utilized to train the classifier. The effectiveness of statistical sampling is demonstrated using the Support Vector Machine (SVM); considering the interval time, the total sampling time is not greater than 1¼ cycles. The suggested approach uses two sampling steps. The first and second steps require a quarter cycle of during-fault and post-fault impedance, respectively. The two phases are said to be separated by a quarter cycle.

[25]The discrete wavelet transform coefficients are used to analyze current data to demonstrate fault classification on a hybrid transmission line. The mother wavelet Daubechies4 (db4) separates the high-frequency components from the fault signals. In the case of a single-circuit single conductor with overhead and underground, a hybrid system combining overhead and underground cable of 115 kV from the Provincial Electrical Authority (PEA-Thailand) system was chosen as the simulated case study. Numerous variables have been considered, including the fault's location, type, and angle. This technique can be improved by incorporating artificial Intelligence to boost accuracy and rescue computation speed, improving protective systems and boosting the dependability of power systems.

With [26] for fault classification, the fundamental component of currents and voltages recorded at only one of the line's ends and the impact of zero-sequence current have been utilized. The data is trained using the Levenberg-Marquardt method, which is a supervised technique. The simulation results demonstrate that the fault categorization is performed appropriately and accurately.

[27] The Continuous Wavelet Transform (CWT) examines traveling waves caused by faults. Conventional and defect transient inferred mother wavelets are used to examine the transient voltage waveform after it has been captured at a measurement point. This method relies on the correlation between typical CWT signal energy and particular network paths that traveling waves caused by faults travel along. As mentioned earlier, the uninterrupted frequency spectrum of fault transients needs to be established to identify specific frequencies directly connected to the routes. The fault's location is then found using this frequency domain information. The fault position is determined from the frequency domain data and theoretically calculated characteristic frequencies. The method of making the transient-based wavelet function orthogonal, which enables the reconstruction of a transient signal for every characteristic frequency, could be studied further.

In order to combine the benefits of a quadrilateral impedance relay with a traveling wave fault locator for fault finding on a mixed overhead and subterranean transmission feeder, [28] employs a Multiple-Zone Quadrilateral Impedance Relay and a Dual-ended Travelling Wave Fault Locator. A modified quadrilateral impedance relay performs well to withstand the impact of fault resistance on the ability to locate and identify the fault section. However, the impedance relay has trouble locating the problem section when a fault happens near a junction where an overhead line joins an underground cable. The traveling wave fault locator now carries out the task of identifying the fault section, and the algorithms for the relevant fault sections are then used to determine the particular fault site.

The initial traveling wave was detected at two ends of the combined line with a set value by comparing the time difference between the arrival time of the fault-induced signal. (CHEN Ping & WANG Kuixin,

2011) classifies and locates the faults in high-voltage overhead lines combined with underground power cables and identifies the fault section on the line. The shortcoming of this method is that it does not consider the multi-reflection of the traveling wave.

[30]Suggests a brand-new framework for data logger-equipped intelligent distribution networks for fault localization and detection. The architecture supports networks containing a combination of underground cables and overhead wires. Faulty section identification, faulty area detection, faulty section identification, and high impedance fault localization make up the suggested framework. First, current relays and digital fault recordings are used to identify the faulty zone and section. The faulty line is then discovered by comparing the measured traveling times at both ends of the lines connected to the protective zone.

Using only single-end data, [31] propose a combination wavelet transform and module artificial neural network-based defect detector, classifier, and locator for six phase lines. The module artificial neural network's input for fault identification and location uses the standard deviations of the approximation coefficients of current and voltage data obtained utilizing discrete wavelet transform. The suggested approach examined 120 different shunt fault forms with variations in their locations, fault resistance, and fault inception angles. The outcome supports the protection scheme's dependability and efficacy, which makes it perfect for real-time application.

In order to extract essential qualities and dynamic elements of the fault signal, [32] use several wavelet-based signal processing algorithms with data collected from the primary feeder current. This method implements an algorithm for fault identification and classification using features taken from wavelet transforms. Depending on the kind of fault, one of four ANFIS-based algorithms is employed to find the fault zone. This method can be entirely independent of fault and line parameters for fault detection and fault type classification. However, the process is made more difficult by employing many algorithms.

[33] employs a two-part neuro-fuzzy system for fault location and classification. One is to use the precise coefficients produced by the wavelet transform to distinguish between the fault segment that is overhead and underground. The other system determines where the fault is. After a fault is found using level 1 coefficients, a neuro-fuzzy system employing level 1 is used to distinguish between an overhead line and an underground cable. One benefit of this approach is that the technique produces valuable results even when the overhead portion has a high impedance fault.

4. Recommendation

Below are some suggestions for areas to research based on the discussion of the various classification systems:

i. If the proposed transmission line classification algorithms may be applied to distribution systems
ii. An in-depth examination of the impedance approach and how it might be combined with the discrete wavelet transform for fault classification

5. Conclusion

Numerous modern fault classification techniques and their distinguishing characteristics are included in this study. These methods have unique advantages, and research is constantly being done to reduce the operation time of relays while operating them at high speeds. Therefore, it is necessary to create new algorithms with improved computational efficiency and adaptability for real-time applications employing sophisticated optimization approaches and flexible alternating current transmission systems (FACTS) devices. Finally, the complete study is anticipated to be helpful for power system protection designers and users of fault analysis.

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