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A Robust Fault Diagnosis Scheme using Deep Learning for High Voltage Transmission Line

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***Abstract*—The transmission lines repeatedly face an aggregation of shunt-faults and its impact in the real time system increases the vulnerability, damage in load, and line restoration cost. Fault detection in power transmission lines have become significantly crucial due to a rapid increase in number and length. Any kind of interruption or tripping in transmission lines can result in a massive failure over a large area, which necessitates the need of effective protection. The diagnosis of faults help in detecting and classifying transients that eventually make the protection of transmission lines convenient. In this paper, the authors propose a deep learning-enabled technique for the detection and classification of transmission line faults. The faulty information are extracted using Discrete Wavelet Transform (DWT) and fed into the multilayer perceptron classification model. The results indicate that the proposed approach is capable of accurately classifying and detecting faults in transmission line with high precision.**

***Index Terms*—High voltage transmission line; Fault Diagnosis; Current and Voltage signal; Discrete wavelet transform; Artificial Neural Network.**

I. Introduction

The transmission and distribution system faults mainly includes line-to-line, single-line-to-ground, double-line-to-ground, and three-phase-to-ground fault. Among them, the major amount of faults, around 70%, are caused due to short circuit faults, which is a form of single-line-to-ground fault. During this faulty state, definite a mount o f r edundant data are carried out by the three-phase signal resulting in intense difficulties i n f ault c lassification fr om th e ra w three-phase signal. This barriers drives the researchers to a method namely feature extraction that enables the extraction of non-redundant data from the raw signal. With the help of this method, voltage and current waveforms are synthesized.

The majority of traditional fault-detection strategies for transmission lines incorporate primarily processing of data focusing on extracting features of post-fault current and voltage signals. In recent years, many researchers have investigated on this topic and introduced approaches intended to improve fault detection operation. The current ratio method, the high-frequency method, the off-harmonic current method, the neural network, and the Kalman filtering method are among the methods developed. Nevertheless, even if many of these strategies strengthens fault detection to some point, they each have their own set of disadvantages. Only several methods have been put through experimental verification to see how effective they are under various system and fault environments.

In current transmission line systems, in which process execution is getting increasingly smarter and fully automatic, intelligent fault diagnosis with minimal user interference is preferable.

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It would indeed be highly beneficial if the tracking device could consistently regulate for disruptions or faults and then make any necessary action depending on the quality and position of the fault in attempt to efficiently a nd precisely mitigate the fault with absolute speed, sensitivity, and accuracy. It would lead to the path of reducing electrical system outages and consumer dissatisfaction. The tracking system generally has a large amount of measured event info collected, which eventually causes manual processing of interpreting the information and taking the appropriate remedial measures nearly infeasible and time-intensive. Manual analysis of information collected is also hampered by the data's feature space and the complication of the discrimination process. The discrimination process becomes extremely unpredictable as the disruption characteristic, length of time, and amplitude elements change. To resolve these issues, it is essential to obtain crucial attributes from unprocessed information and work with information that is controllable in magnitude.

Transmission line faults take place arbitrarily and individually, fault diagnosis provide a viable approach for discovering and closing off the faults in power systems. This can anticipate appropriate groundwork for fault detection, such as upgrading the tranmission design process, adjusting the configurations and enhancing the distribution architecture [1]. Moreover, it directs the operatives to assess efficient a ctions i n t he earlier phases of processing inverter malfunction, also mitigating the risk of catastrophe faults and reducing maintenance costs [2]. Diagnosis of faults involve several stages as follows: determination, isolation and classification. T he p rimary o bjective of determination is to evaluate the severity of faults in a system. Once the fault information is assessed, it is possible to achieve fault isolation. The exact position of the faults is discerned by fault isolation. And the final s tage d escribes t he features of the fault and specifies t he f ault m easures. I n b road terms, fault diagnosis techniques can be classified a s model-based techniques, signal-based techniques and artificial-intelligence techniques [3]. Numerous research has been conducted based on these techniques for the purpose of achieving efficient fault diagnosis.

Model-based techniques embodies the basic fault attributes of any system, although they rely on the availability of a certain model and parameters. Multiple deterministic, stochastic and discrete-event model-based techniques have been developed for such as stator current nonlinear observer, adaptive observer, descriptor observer, sliding mode observer (SMO), linear parameter varying (LPV), extended kalman filter (EKF), parity relation, parameter estimation and so on [4]. An et al. [5] implied a quick diagnostic method without sensors by analyzing the switching-function model of inverter under faulty conditions. It uses the collector-emitter voltages from lower power switches of the inverter to detect open-circuit faults, though the effect of loads have severe impact on the diagnosis. In [6], authors suggest a stator current nonlinear observer to identify open-circuit actuator faults in the power inverter in an induction motor drive based on residual generation. Regardless, accurate parameters are needed, and the scheme is required to be upgraded for application in multilevel inverter topologies. Reference [7] proposed an approach based on SMO and a half-bridge switching model to speculate the position of fault in modular multilevel inverters, although the measurement precision is limited when the error is larger and in the presence of nonlinearity. In [8], authors proposed an open-circuit fault diagnosis for VSIs using a model reference adaptive approach. Using the observed voltage distortions, fault recognition is obtained because the voltage distortions are dissimilar as per the defective part. However, this method was heavily reliant on the estimation of parameters. The concept of the model-based fault diagnosis techniques is to build suitable system models and thereby attain the diagnosis of faults with precision. Although, the sophistication of model-based techniques makes it increasingly hard to build a coherent model for complex systems and diverse fault occurrences.

In contrast, signal-based techniques use measurement of signals for fault diagnosis instead of direct input-output models. Utilizing time domain, frequency domain and time-frequency domain, the measurement study is performed for phases or spectrum, amplitudes and signal deviations. Signal-based methods include fast fourier transform (FFT), hilbert huang transform (HHT), winger ville distribution (WVD), park's vector method, current average value, current residual, load current analysis etc. In [9], authors proposes a open-circuit fault diagnosis for PWM-VSI fed induction motor drive using three-phase output current residuals. The residuals would be higher than a pre-defined threshold once the fault is detected. However, the tuning effort in this effort is required to be more optimized. Zhang et al. [10] used a simplified approach for VSI open-circuit fault detection of both single and double switches, using the load current analysis method. It applies the calculation of operating states of the motor drive to locate the fault. The accuracy of this method is affected by imprecise value estimations. Reference [11] used a combined strategy by means of WVD and empirical-mode decomposition. Intrinsic mode functions are investigated by WVD for the diagnosis of short-circuit faults in PMSM drives. Anyhow, this method is disrupted by cross-term interference due to various signal components. The method in [12] used absolute phase current mean value to embody diagnosis parameters to determine open-circuit inverter faults. Another combined method in [13], used FFT and principle component analysis (PCA) for also open-circuit fault detection. These methods are sensitive to thresholds and lacks of adaptability and time-domain data. Moreover, all the signal-based techniques is not quite suitable for unhealthy conditions, load variations and external noise.

To overcome the challenges, this study proposes a fault diagnosis methodology that captures the generated current waveforms from transmission line during fault conditions. The authors have applied Artificial Neural Network (ANN) with Discrete Wavelet Transform (DWT) and demonstrated that it enhances the effectiveness of the fault diagnosis operation. The advantages of this method are as follows:

- Capable of identifying particular features in a waveform. Wavelets of small sizes can be utilized to distinguish quite essential features in a waveform, while wavelets of large sizes can be employed to classify rough information.
- In contrast to other approaches, achieving a reasonable estimate from fault transients with just a few wavelet coefficients is a huge accomplishment.
- Other signal analysis methods neglect features of data such as patterns, breakdown points, and dislocations in elevated variables and self-similarity, whereas DWT denoise signals comprising various range of features.
- Competence to deal with insufficient information: After Training process, the information can provide output even if the knowledge is inadequate. The amount of productivity lost here is determined by the relevance of the incomplete data.

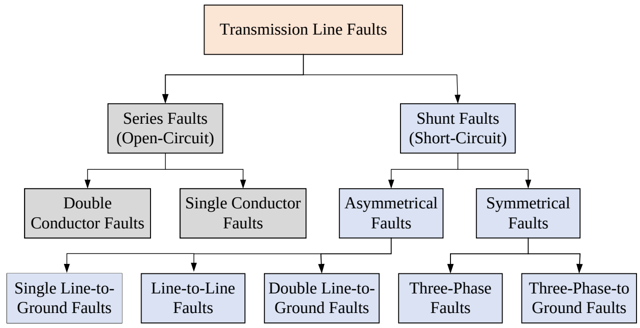


Fig. 1: Differents types of faults in transmission line.

The rest of the paper is structured in the following manner. Section 2 represents the materials and method of this research. The modeling of the power system with details of the various type of fault is reported in Section 3. Section 4 presents the feature extraction operation. The layout of the suggested approach for classifying three phases fault is depicted in Section 5. Section 6 covers the result assessment of the proposed framework under various attributes. The conclusion and future scopes of the paper is in Section 7.

II. Materials and Method

A. Types of Transmission Line Faults

The variance of voltages and currents from set points are simply can be referred to as faults in power transmission [14]. Electrical grid equipment or transmission and distribution lines bear regular voltages and currents under standard conditions, resulting in a process that is safer to operate. However, whenever a fault arises it triggers extremely high currents to flow, resulting in infrastructure and system disruption. Transmission line faults can be caused by a variety of factors, including severe weather that disrupts electricity and damages electrical systems, as well as equipment failures that allow high current to pass through appliances [15]. Furthermore, ionization of the air around overhead power lines caused by smoking material resulting in a flare in between lines or between conductors and insulator. Due to excessive voltages, insulators weaken their insulting potential during a flashover. The effects of electrical faults are massive. Such as, when a fault occurs, the overcurrent flow is forced into a low impedance channel [16]. As a result, a large amount of current is pulled from the flow which causes disconnecting relays and insulation failure among the devices in transmission and distribution system. Moreover, people can get shocked by the appearance of a fault. The magnitude of the shock is determined by the

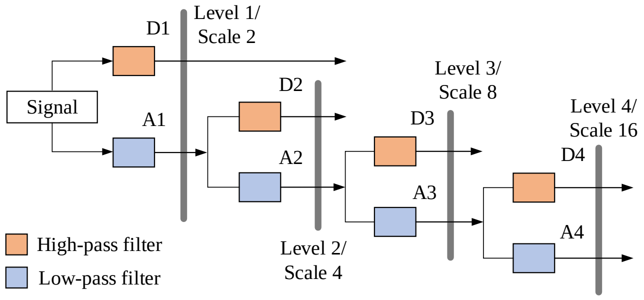


Fig. 2: Wavelet transform decomposition scheme.

voltages and currents at the fault site, and it may also end in injury. Because of the high current generated by transmission line faults, the devices are totally wiped out, resulting in inappropriate operation of the apparatus or system. Serious fires will force all the appliances to completely flame out. Besides, faults influence not just the place where they appear, as well as the functional intertwined networks that are linked to the applauded thread. In addition, Owing to the charged particles of atmosphere across conductive metal paths, a fault in transmission line can create corrosion and flares, which can result in serious burning [17].

However, there are primitively two types of faults in the power transmission lines, as shown in Fig. 1. Those are series faults and shunt faults [18]. In the faulted phase, series faults are accompanied by a rise in voltage and frequency, as well as a decline in current. On the other hand, shunt faults result in an increase in current with a reduction in frequency and voltage. Shunt faults are basically short circuit faults, which are categorized into: (i) Symmetrical faults, which are extremely serious faults that take place less often in transmission lines. They are alternatively termed as balanced faults and are of two sorts, which are three phase faults (L-L-L) and three phase-to-ground faults (L-L-L-G). (ii) Asymmetrical, which are less drastic than symmetrical faults and more familiar. There have been primarily three sorts which are single line-to-ground (L-G), line-to-line (L-L), and double line-to-ground (L-L-G) faults. L-G fault is the many common form of fault accounting for 65-70% of all faults. It allows the wire to come into interactions with the ground or earth. L-L-G faults account for 15-20% of all faults, causing the two transmission lines to make connection to the earth. L-L faults happens when two conductors collide with one another, usually because when lines are whipping extreme weather conditions, and account for 5- 10% of all faults [19].

B. Theory of Wavelet Transform Analysis

Wavelet transform methods have been successfully employed for multi-scale presentation and evaluation of current and voltage in previous times, usually applied to detect quick changes in signal transients. It deteriorates transients to a sequence of wavelet elements, which itself is a time-domain pulse that encompasses a particular frequency band and contains additional details [20]. It also locates data in the time–frequency axis, and they're particularly good at exchanging each sort of resolution to other, which making them appropriate for non-stationary feature extraction of a specific window. This technique separates measurements into various frequency elements, which it then analyses with a resolution that corresponds to its size [21].

Wavelet transform is categorized into two types: continuous wavelet transform and discrete wavelet transform (DWT). In DWT, digital filtering methods are used to create a time-scale depiction of a digital signal, where the signals are analysed at various scales using filters with various cut-off frequencies. To assess the high frequencies, the signal is put through a sequence of high-pass filters, and to assess the low frequencies, it is filtered through a sequence of low-pass filters. Therefore, the signals are split into two categories of features, which are termed as detail (high-frequency and low-scale features) and approximation (low-frequency and high scale features) [22]. This process of decomposition can be repeated, with consecutive measurements decomposed one after the other, until each signal is dissolved into several smaller resolution components. A visual representation is shown in Fig. 2. However, there exist many types of wavelets such as Haar, Daubechies, Biorthogonal, Coiflets, Symlets, Morlet, Mexican hat, and Meyer [23]. The Daubechies wavelet is amongst the most powerful DWT tools in the DWT group, which has been employed to obtain useful attributes from captured signals. They're commonly utilized to solve a multitude of issues such as determining a signal's self-similarity characteristics or nonlinear issues, detecting signal divergences and so on. There are Daubechies levels ranging from level 2 (db2) to level 20 (db20), in which the frequency distribution corresponds to the total count of parameters [24].

III. System Investigation

To design the $3-\varphi$ electrical networking system included in Figure 3, a 220 kV, 50 Hz transmission line containing a extent of 100 km was employed. In a MATLAB environment, the network connection is constructed, offering real - time equipment to prepare and analyze the desired information for conducting the fault diagnosis process. The constructed channel's transmission lines are linked to 2 sources and have positive sequence resistance of 0.01273/km and zero sequence resistance of 0.3864/km. With a sampling frequency of 20 kHz, the line voltage and current waveforms are measured from the bus on the source-1 end. The frequency is differed again to assess the suggested method's classification results. The current and voltage waveforms obtained from the system provide the necessary information for identifying and locating faults occurring in the corresponding transmission line. Ten categories of faults have been computed for different system parameters as depicted in Fig. 3, in order to acquire the required information for the diagnosis operation. Some additional system parameters of the model is included in Table 1.

A. Data Processing

The "non-faulty" waveform is taken as a normal condition-based fault category for the fault diagnosis process, resulting in a combination of eleven fault categories when all faults and the "non-faulty" state are combined. In at normal phase the system quality is expected to be "nonfaulty." Once the system performance adjusts to a specific form of fault, the fault is shown to have identified. The DWT method necessitates the feature extraction from data derived from unprocessed voltage and current waveforms. Depending on the process conditions, each fault has a distinct category of waveform.

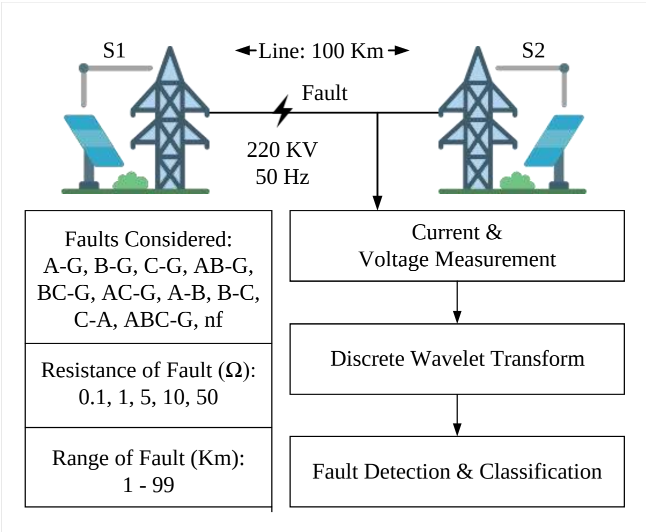


Fig. 3: Studied model with system parameters.

For various fault resistor and fault lengths, the transmission line with all fault categories is designed to simulate. At a sampling frequency of 20 kHz, the simulation is conducted for 1.5 seconds.

Regarding the dataset the authors have used, contains 396 samples for each class, where there exist 11 class. The total dataset therefore contains 4356 samples of data. The authors have applied the dataset's 70% for training and 30% for testing.

TABLE I: Additional system parameters of the tranmission line network.

System Parameter	Types/Values
Pre-fault Angle	30 degree
Zero and Positive Sequence Resistances (Ohm/km)	0.3864 and 0.01273
Zero and Positive Sequence Inductances (H/km)	4.1264e-3 and 0.9337e-3
Zero and Positive Sequence Capacitances (F/km)	7.751e-9 and 12.74e-9
Phase-to-phase Voltage	220 kV
Base Voltage	220 kV
Base Power	60 MVA

B. Fault Effects

Faults can occur everywhere along a transmission network in operation. The framework will measure the signal at whichever position along the transmission line using the envisaged model with a multitude of fault distances. The fault position is ranged from 1 km to 99 km for data preprocessing, and the subsequent voltage and current waveforms are measured. The fault resistance is adjusted to 10 in this experiment, and the other system variables are maintained constant. The fault resistance is yet another system metric that has a significant effect on the detection task. If the fault resistance is not taken into account, earth faults may result in inaccurate signal calculations. In particular, the current system has been tested with variability in fault resistance to demonstrate that it can successfully analyse and classify line faults. The fault distance is maintained consistent at 50 km from the measurement end, and all other system parameters are maintained unchanged while analysing the influence of fault resistance on the signals.

IV. Feature Extraction

The three-phase signals are evaluated from the transmission line system when the faulty scenario takes place, which are the basically expressions of the fault conditions. This evaluation of fault data means that the signature data can be used to ascertain the exact phase that precipitated the fault. It is difficult to take into consideration for the raw three-phase waveforms because the signals have a large number of recorded sample points. As a result, this research converts the raw time-domain transients into wavelet-packets for the feature extraction method with a view to obtain the most appropriate input features. In this study, the post-fault frequency signals are naturally interpreted for addressing the detection challenge. On the other hand, the waveforms are not taken lengthy for analysation because they increase the system's simulation time.

In DWT, a non-stationary transient is evaluated at multiple scales using different threshold frequencies of digital filters. A time-domain signal DWT(t) is decayed into approximations (A) using a series of high-pass filters by using father wavelet W(t). Likewise, the mother wavelet X(t) ultimately translates the signal into comprehensible variables within a sequence of low-pass filters.

$$W_{\alpha\beta}(t) = 2^{-\frac{\alpha}{2}} W\left(2^{-i}t - a\right) \tag{1}$$

$$X_{pq}(t) = 2^{-\frac{\alpha}{2}} X\left(2^{-i}t - a\right) \tag{2}$$

The numbers α and β are integers here, with an indicating the units of time to which the functions are transcribed and 2^a indicating the scale functions, which are obtained from the following variables:

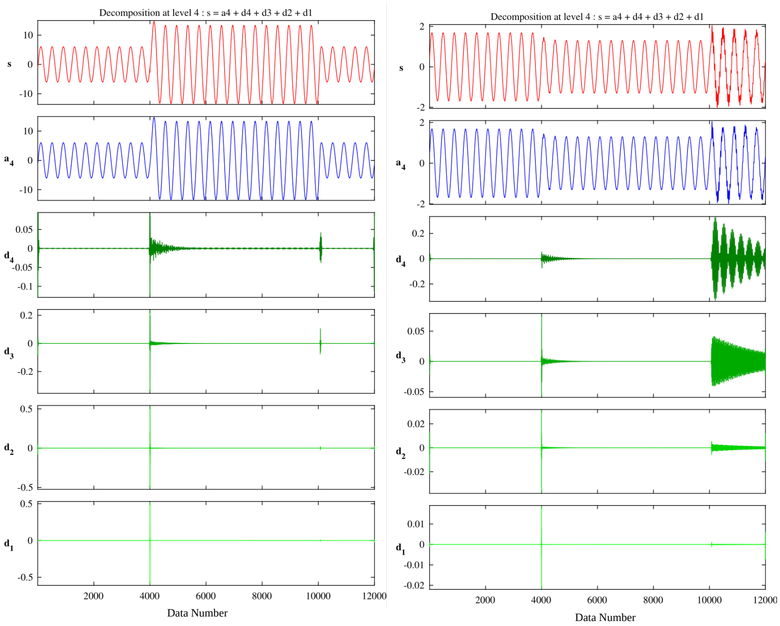
$$W(t) = \sum_n P(a)\sqrt{2}W(2t - a) \tag{3}$$

$$X(t) = \sum_n Q(a)\sqrt{2}X(2t - a) \tag{4}$$

$P(a)$ and $Q(a)$ denote two filter-coefficients, respectively. The wavelet transform performance can be described as follows if the N decomposed stage is accounted:

$$DWT(t) = \sum_{\beta=0}^{2^{N-\alpha-1}} A_{\alpha\beta}W_{\alpha\beta}(t) + \sum_{\alpha}\sum_{\beta=0}^{2^{N-\alpha-1}} D_{\alpha\beta}X_{\alpha\beta}(t) \tag{5}$$

At the i decomposition stage, the results of high pass filters and low pass filters are sub-shifted by a vector of 2 and result in an approximation A and detail coefficients D. The process is reiterated before the A and D coefficients at level five have been determined. However, In previous studies, the daubechies (db) mother wavelet has been found to be the most suitable for power system signal analysis. Hence, the db at 4th order (db4) was chosen for this application. Considering the absence of an irregular implementation, other wavelets such as the Marr (Mexican hat), Meyer, and Morlet wavelets are not inspected in this research.



(a) (b)

Fig. 4: Feature extraction using DWT for A-G fault: (a) current signal feature extraction, (b) voltage signal feature extraction.

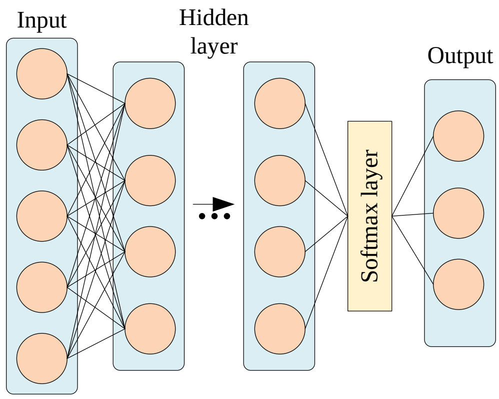


Fig. 5: Architecture of ANN classification model.

V. Proposed Methodology

In this research, the authors employ ANN as the method to classify fault classes. Input layer, hidden layer, softmax layer, and output layer are the four kinds of layers in a basic neural network for supervised learning, as shown in Fig. 5. Upon being supplied through towards input layer, input data must be standardized, as is common of real - time fault diagnosis approaches. Applying the pattern normalization of the governing equations to all variables in the span [0,1] is one option:

$$f' = [x - \min(f)][\max(f) - \min(f)]^{-1} \tag{6}$$

The preceeding variational modifications convert the data embedded in the data input into relatively high interpretations (i.e. attributes) in the hidden units:

$$\begin{aligned} J_n &= \delta\left(K_n f + c_n\right) \\ J_n &= \delta\left(K_n J_{n-1} + c_n\right), n = \{2, \ldots, q\} \end{aligned} \tag{7}$$

where, f and J_n are the input and hidden vectors, respectively, K_n and c_n are the weight-matrices and bias values, respectively, and q is the no of hidden units. Mentioning, $N_{J}n$ (i.e. no. of nodes in each hidden unit) and q are hyper-parameters whose magnitudes require to be examined before the training of ANN. δ is a nonlinear activation function that performs the mentioned conversion , and in this research, the authors utilize the rectified linear unit (ReLU) which is determined as:

$$\delta(f) = \max(0, f) \tag{8}$$

The result throughout the final hidden units is subjected to a conversion without the activation function, which caqn shown as:

$$J_p = K_p J_q + c_p \tag{9}$$

The softmax layer uses the softmax function of the governing equations to estimate the weights of each output node:

$$X_i = \frac{\exp\left(J_{p,i}\right)}{\sum_{i=1}^{N_{J}p} \exp\left(J_{p,i}\right)} \tag{10}$$

The model then chooses the labeling with the highest expected score to apply a determined selection to the input information.

VI. Performance Evaluation of Fault Detection

A. *Decomposed Current & Voltage Waveforms*

Several customary findings are shown in this section to show how the fault occurrence developed virtually. As previously stated, the MATLAB Simulink environment was used to generate separate sorts of faults. The ten different types of short-circuit faults include: (i) Single line-to ground fault connecting a line from any of the three phases to ground (i.e., A-G, B-G, and C-G), (ii) Double line-to ground fault connecting two lines from any of the three phases to ground (i.e., AB-G, BC-G, and AC-G), (iii) Line-to-line fault connecting two lines with each

TABLE II: Statistical data regarding decomposed current waveforms.

Fault	Phase A (Current)			Phase B (Current)			Phase C (Current)		
	Max	Min	Std	Max	Min	Std	Max	Min	Std
A-G	14.7	-13.37	7.365	6.048	-6.048	4.277	6.048	-6.048	4.277
B-G	6.048	-6.048	4.277	13.4	-13.4	7.342	6.048	-6.048	4.277
C-G	6.048	-6.048	4.277	6.048	-6.048	4.277	13.44	-13.75	7.362
AB-G	25.11	-22.09	11.52	18.33	-21.39	9.713	6.048	-6.048	4.277
BC-G	6.048	-6.048	4.277	22.38	-22.11	11.59	18.32	-18.85	9.713
AC-G	21.02	-18.33	9.704	6.048	-6.048	4.277	22.09	-24.04	11.51
A-B	24.74	-21.91	11.43	17.47	-20.78	9.323	6.048	-6.048	4.277
B-C	6.048	-6.048	4.277	22.25	-21.92	11.48	17.49	-17.9	9.325
A-C	19.93	-17.47	9.297	6.048	-6.048	4.277	21.91	-24.03	11.42
ABC-G	26.19	-22.61	11.8	22.61	-24.1	11.74	22.63	-24.08	11.73
Normal	6.048	-6.048	4.277	6.048	-6.048	4.277	6.048	-6.048	4.277

other from any of the three phases (i.e., A-B, B-C, and A-C), and (iv) Three phase-to-ground fault connecting all three lines to ground (ABC-G). Here, phase A, phase B, phase C, and ground are represented by the characters A, B, C, and G, respectively. The discrete wavelet transform (DWT) was used as an efficient strategy for extraction and post-processing of important attributes from fault behaviours for convenient categorization in the current study.

The most familiar category of fault is a single line-to-ground fault, which is generally the lowest disruptive to the system. The faulted phase current can be anywhere from zero to marginally higher than the three-phase fault current within this type of fault. Line-to-ground faults that have intensified to have a second phase conductor are known as double line-to-ground faults. This is a fault that is unbalanced, whereas the fault currents are typically bigger than line-to-line fault currents, but smaller than three phase fault currents. The fault current of a line-to-line fault is rarely calculated for equipment ratings though since it does not offer the maximum fault current magnitude. The three-phase-to-ground fault happens if three lines are ratcheted up next to each other and also have fittings to the ground. All these faults can result in obnoxious circulating currents or activate electronics enclosures at hazardous voltages. As an example portray, Fig. 4 show observations of the sampled current and voltage signals for phase A respectively, due to A-G single line-to-ground fault. From the figure it is seen that, that fault occurrence went from the data points of 4000 and stayed upon to data points of 10,000; causing severe transients in both voltage and current waveforms. Table II shows the statistical data for all the classes regarding three-phase current information. The data includes detailed coefficient maximum, minimum, and standard deviation values for 12,000 data points. These data are to indicate at which phase the fault has taken place.

B. Results Assessments

The results of our proposed classification model has been depicted based on accuracy (Acc), precision (Pr), recall (Re), and f1-score (F1). These metrics are calculated based on True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) values. These indicate the instances that are properly predicted. The most instinctive efficiency metric is accuracy, which is essentially the proportion of properly predicted observational data to all findings.

$$Acc = TP + TN/TP + FP + FN + TN \tag{11}$$

The overall accuracy (OA) for this classification model is found as 99.3%.

The proportion of properly predicted positive findings to net anticipated positive findings is known as precision. The overall precision found for this classification model is 0.99.

$$Pr = TP/TP + FP \tag{12}$$

The proportion of properly anticipated positive findings to all observations in the exact class is known as recall. The overall recall found for this classification model is 0.99.

$$Re = TP/TP + FN \tag{13}$$

The measured avg of Precision and Recall is the F1-Score. As a result, this score considers both false positives and false negatives. The overall F1-Score found for this classification model is 0.99.

$$F1 = 2 * (Re * Pr)/(Re + Pr) \tag{14}$$

The authors also depict our results regarding correct classifications and missclassifications using a matrix in Fig 6., where the instances in an true class are represented by the rows of the matrix, while the instances in a predicted class are represented by the columns.

Model Prediction \ Actual Fault States	AG	BG	CG	ABG	BCG	CAG	AB	BC	CA	ABCG	NF
NF	**106**	0	**4**	0	0	0	0	0	0	0	0
ABCG	0	**126**	0	0	0	0	0	0	0	0	0
CA	0	0	**138**	0	0	0	0	0	0	0	0
BC	0	0	0	**130**	0	0	0	0	0	0	0
AB	0	0	0	0	**96**	0	0	0	0	0	0
CAG	0	0	0	0	0	**117**	0	0	0	0	0
BCG	0	0	0	0	0	0	**119**	0	0	0	0
ABG	0	0	0	0	0	0	0	**110**	**1**	0	0
CG	0	0	0	0	0	0	0	0	**110**	0	0
BG	0	0	0	0	0	0	0	0	0	**123**	0
AG	0	0	0	0	0	0	0	0	0	0	**123**

Fig. 6: Classification performance of the proposed network.

C. Comparative Study

This section compares the proposed method to a number of other fault diagnosis methods that are currently available. To evaluate the energy density of frequencies, traditional methods used fourier evaluations to convert data into frequency domain. Nevertheless, some rather assessments may provide data in either the frequency or time domains, not each of the two at the identical period. Despite the fact that the wavelet transform was created to address the issue by displaying frequency and energy information in the time domain, it hardly struggles from the topology of leading up finite elements with the initial signal. The Hilbert Huang Transform, on the other hand, can provide data on intensity and power information in the spatial domain without measures that ensure filter banks. Its ability to delineate various elements in narrow-band frequencies, however, is constrained. The narrow spectrum can sometimes incorporate elements with adjoining frequencies or elements with different frequencies but a far greater power frequency than the others. The wavelet transform, on the other hand, is frequently compared to other methods. The Fourier transform, for instance, is a useful tool for digital signal processing that are made up of a mix of sine and cosine signals. In non-stationary signal analysis, the Fourier transform is less beneficial. The elements of a non-stationary signal can be assessed using wavelet transforms. Wavelets also make it possible to create filtration for both stationary and non-stationary signals. Outside of traditional signal processing, the Fourier transform appears in a surprising number of places. Even with this in view, we believe it is correct to conclude that the arithmetic of wavelets outnumbers the arithmetic of the Fourier transform. In fact, the Fourier transform is included in wavelet maths. Wavelet theory is proportional to the width of the applicability. Spectrum analysis and filtering were the first wavelet implementations. However, comparison with other methods, ANN with DWT is depicted on quantitatively in Table III.

TABLE III: Comparison of wavelet transform with different methods.

Method	Advantages	Disadvantages
Symmetrical Component	Simple operation; Ease of utilization; Less complexity	Less accuracy; Narrow amount of classification types
Fourier Transform	Less information is lost; Easy implementation	Arbitrary decision thresholds; Lack of efficiency
Empirical Mode Decomposition	Self-adaptive; Data driven	Additional noise; Mode-mixing; Access computation
Hilbert Huang Transform	Discernible particular data structures	Data validation not ensured; Distorted data extraction
Wigner Ville Distribution	Finite support; Fast	Inadequate representation; Accuracy not ensured;
DWT+ANN	Direct analyzation of fault; Highly elegant; Precise computation; Better performance during noise; Need less heuristics	

VII. Conclusion & Future Scopes

This paper utilizes wavelet transform for identifying and categorizing of transmission-line faults. The proposed process uses three-phase current waveforms for detection and classification processes. To enhance the reliability of the strategy, the waveforms of the signals are obtained with the variability of the transmission line element, which is then evaluated with ANN. The implemented approach has the significant advantage of being able to sequentially gather data from fault details, which enhances the system's generalizability. The study results of this research show that the suggested technique accurately classifies faults for all types of faults. The outcome of different sample frequencies and signal types included showcases that using current within the frequency range perceived can produce desired outcomes. A comparison of the proposed method to the conventional methods is discussed, with the conclusion that the proposed method produces more consistent and reliable results. Some future scopes include:

- Accurate data gleaned by systems installed in the operational electrical grid may be taken into account in the classifier's future development.
- The actual system information obtained by the measurement system equipment and enlisted in a real-world electricity network may be reflected in the practical improvement of this investigation.

However, this research is expected to provide prudent support for researchers in the corresponding field. Transmission line fault wavelet analysis could include using real-world data, taking into account various types of transmission line impedance and series faults, and comparing other deep learning architectures to evaluate performance across a broad domain. As a result, all methods used in the transmission line domain must be experimentally validated to ensure their effectiveness.

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