A Robust Fault Detection Scheme Using Wavelet Analysis for High Voltage Transmission

Sazzed Mahamud Khan, and Abu Hena MD Shatil

***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 helps in detecting and classifying transients that eventually make the protection of transmission lines convenient. In this paper, we propose a Discrete Wavelet Transform (DWT) based technique for the detection and classification of transmission line faults. The results indicate that the proposed approach is capable of accurately classifying and detecting faults in transmission line with high precision.**

***Keywords*— high voltage transmission line; faults; current and voltage signal; discrete wavelet transform.**

1. Introduction

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 transmission design process, adjusting the configurations and enhancing the distribution architecture. Moreover, it directs the operatives to assess efficient actions in the earlier phases of processing inverter malfunction, also mitigating the risk of catastrophe faults and reducing maintenance costs. Diagnosis of faults involve several stages as follows: determination, isolation and classification. The primary objective 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 stage describes the features of the fault and specifies the fault measures. In broad terms, fault diagnosis techniques can be classified as model-based techniques, signal-based techniques and artificial-intelligence techniques (Bhuiyan et al.,2020). Numerous researches have 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 (Gao et al., 2015). An et al. (An et al., 2010) 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 has severe impact on the diagnosis. In (Campos et al., 2010), 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 (Shao et al., 2013) 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 (Jung et al., 2012), 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

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American International University-Bangladesh, Dhaka 1229 (e-mail: smkhan500@gmail.com, abu.shatil@aiub.edu).

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 (Wu et al., 2015), authors propose an 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. (Zhang et al., 2014) 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 (Rosero et al., 2018) 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 (Zhao et al., 2017) used absolute phase current mean value to embody diagnosis parameters to determine open-circuit inverter faults. Another combined method in (Wang et al., 2015), used FFT and principal 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 are 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. We have applied 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.

The rest of the paper is structured in the following manner. Section 2 and section 3 represents the types of transmission line faults and theory of wavelet transform, respectively. The modeling of the power system with details of the various type of fault is reported in Section 4. The layout of the suggested DWT 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.

2. Types OF Transmission Line Faults

There are primitively two types of faults in the power transmission lines, as shown in Figure 1. Those are series faults and shunt faults Fahim et al., 2021). 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.

3. Theory OF Wavelet Transform

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 It 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 analyzed 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). 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. However, there exist many types of wavelets such as Haar, Daubechies, Biorthogonal, Coiflets, Symlets, Morlet, Mexican hat, and Meyer. 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.

4. System Investigation

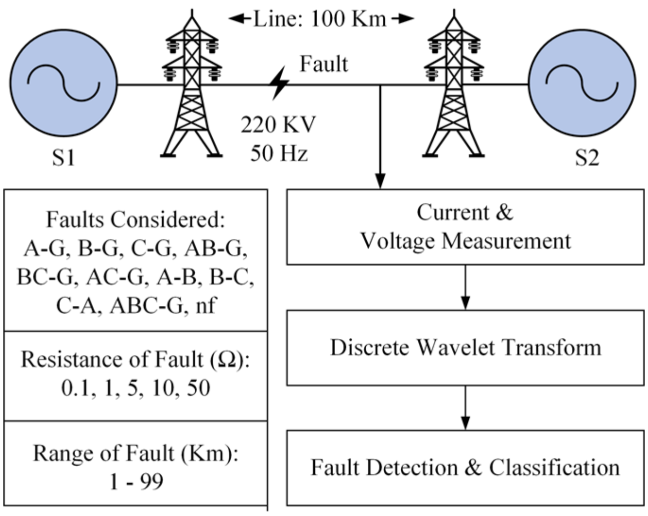

Fig. 1. Studied model with system parameters

To design the three-phase electrical networking system included in Figure 1, a 220 kV, 50 Hz transmission line containing an 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. 1 in order to acquire the required information for the diagnosis operation. Some additional system parameters of the model are included in Table I.

4.1 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. 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.

4.2 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 pre-processing, 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 analyzing the influence of fault resistance on the signals.

5. Proposed Methodology

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 analyzation because they increase the system's simulation time.

TABLE I
ADDITIONAL SYSTEM PARAMETERS OF THE TRANSMISSION 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

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.

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

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

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

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

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

The 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:

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

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.

6. Performance Evaluation

6.1 Decomposed Waveforms

A single line-to-ground fault is the highest common type of fault, and it is the least detrimental to the operation. The MATLAB Simulink platform was utilized to produce several types of faults, as earlier described.

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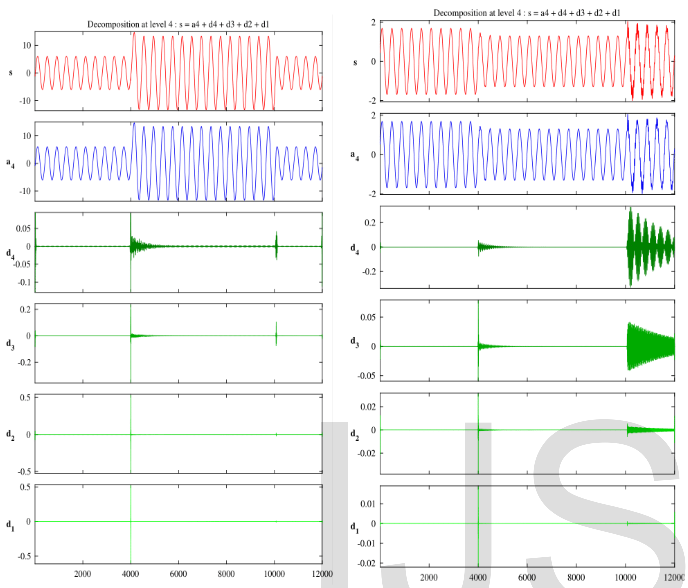
Figure 2 shows findings of the measured current and voltage signals for phase A owing to an A-G single line-to-ground failure, as a sample. The figure shows that the fault event increased from 4000 sample points to 10,000 sample points, resulting in catastrophic pulses in both voltage and current amplitudes. Table II presents the statistical information for all three-phase current data categories. The information contains 12,000 sample points with comprehensive parameter maximum, minimum, and standard deviation measurements.



(a) Current waveform decomposition. (b) Voltage waveform decomposition

Fig.2. Signal decomposition using DWT for A-G fault. (a) Current Waveform Decomposition, (b) Voltage Waveform Decomposition

6.2 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. Wavelet theory is proportional to the width of the applicability. Spectrum analysis and filtering were the first wavelet implementations. However, comparison with other methods, wavelet transform is depicted on basis of some factors in Table III.

TABLE II
STATISTICAL DATA REGRADED 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

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;
Wavelet Transform	Direct analyzation of fault; Highly elegant; Precise computation; Dimension of solution can be reduced; Data compression: Better performance during noise; Need less heuristics	

CONCLUSION AND FUTURE SCOPE

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 DWT. 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:

- Machine learning and artificial intelligence-based techniques can be integrated with DWT to precisely classify various types of faults.
- 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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