

## Article

# Fault Detection on Power Transmission Line Based on Wavelet Transform and Scalogram Image Analysis

Ahmed Sabri Altaie <sup>1</sup>, Ammar Abbas Majeed <sup>1</sup>, Mohamed Abderrahim <sup>1,\*</sup> and Afaneen Alkhazraji <sup>2</sup>

<sup>1</sup> Department of System Engineering and Automation, University Carlos III of Madrid, Avada de la Universidad 30, 28911 Leganes, Madrid, Spain; ahmed.altaie@alumnos.uc3m.es (A.S.A.); ammarabbasmajeed.al-rubaye@alumnos.uc3m.es (A.A.M.)

<sup>2</sup> Communication Engineering Department, University of Technology-Iraq, Al-Sina'a St., Baghdad 10066, Iraq; afaneen.a.abbood@uotechnology.edu.iq

\* Correspondence: mohamed@ing.uc3m.es

**Abstract:** Given the massive increase in demand for electrical energy, particularly owing to global climate change and population expansion, as well as the development of complicated electrical systems due to the urgent need for a sophisticated component to enhance power delivery, it becomes important to adopt a smart and contemporary approach that is also appropriate for the aim of protecting transmission lines (TLs) and ensuring the continuous delivery of electric power to customers. Consequently, a unique and highly reliable approach for identifying faults in TLs is presented in this work, which employs Wavelet Transform and is evaluated using Matlab simulation. Wavelets of various kinds were utilized to demonstrate their dependability. Furthermore, utilizing this approach has shown itself to be highly successful and has yielded spectacular results even when it is used on a complicated electrical network. Moreover, many types of faults were presented and afterward evaluated and verified for the network in various settings, which also demonstrated their potential to recognize faults within a relatively short space of time. This innovation will alter the idea of fault detection by providing a complete and integrated model for detecting faults in a TL, and it may be regarded as a revolution in the renewal of core principles in TL protection.

**Keywords:** transmission line; fault detection; wavelet transform; image processing; power system protection



**Citation:** Altaie, A.S.; Majeed, A.A.; Abderrahim, M.; Alkhazraji, A. Fault Detection on Power Transmission Line Based on Wavelet Transform and Scalogram Image Analysis. *Energies* **2023**, *16*, 7914. <https://doi.org/10.3390/en16237914>

Academic Editors: Akhtar Kalam and Seyed Morteza Alizadeh

Received: 20 October 2023  
Revised: 26 November 2023  
Accepted: 30 November 2023  
Published: 4 December 2023



**Copyright:** © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

## 1. Introduction

Electric power reliability and resilience is a paramount component to any successful economy and a vital requirement for the smooth running of people's lives and businesses. The most important aspect of detecting and isolating faults in electric power systems is to reduce the effect of, or at least mitigate, the losses that can occur with power disruption. Faults can lead to the disastrous collapse of the entire electric power system if they are not discovered and isolated precisely in a very-short time [1]. In recent years, several TL protective techniques and algorithms have been adopted, which are based on trustworthy scientific fault identification theories such as [2–5]. However, such approaches are seen to be insufficient, particularly the extended time required to detect and isolate faults. As a consequence, a variety of recent theories and algorithms have been used to improve the protection of electric power systems and particularly transmission lines (TLs) [6–8], which are more prone to failures due to their length and their outside exposure. A TL protection scheme must be comprehensive and general, and it should apply to the majority, if not all, types of transmission systems, such as those with power factor correction, compensators, load, transformers, and other components. Seeing their importance, the development of TL protection systems is an active research subject, especially with the increasing complexity of such systems.

Many attempts to obtain the best protection systems are based on altering the system stability and incorporating many realistic variables [9–17]. In addition, the hurdles and difficulties associated with such systems to achieve efficient faults detection increases with the complexity of transmission networks. Therefore, it is crucial to develop systems capable of detecting and isolating faults in different power transmission networks, irrespective of the internal network variables. This includes networks containing loads, transformers, series compensators, and other components. It is also very common to ignore certain types of faults, which are less important, and concentrate on a single category of TL issues. However, this can be seen as a weakness of the overall protection system. In general, most research has been focused on shunt faults while ignoring series faults (except very few cases such as [18]), which are seen as non-totalitarian. Therefore, the quest for more general, comprehensive, and integrated systems is a worthwhile objective.

Studies regarding transmission line protection are based on either a single theory [7,11,12,19–23] such as ANN, WT, SVM, and others, or a combination of theories [24–29] such as (WT and ANN), (WT combined with fuzzy logic), (DWT, FT and ANN), and others. Artificial Intelligence (AI)-based transmission line protection is the most widely used approach nowadays due to its comprehensive outlook and efficiency. Artificial Neural Network (ANN)-based algorithms have the capability of training and learning the system's behavior in a variety of settings with great outcomes [7,24,30–32]. Support Vector Machine (SVM) is also used for fault diagnosis, in which it can detect faults, but the results can be severely affected with noisy signals [33]. Fuzzy logic-based algorithms for nonlinear systems can also be used; however, they can give wrong results since they involve inadequate assumptions [21,26,27]. Moreover, the Synchronized Phasor Measurement Unit (SPMU) is used in improving TL protection, but the main drawback is the reduced quality of the data used and communications [15,34,35].

Numerous fault identification methodologies have been explored for transmission lines (TLs), each offering distinctive contributions to the field. Kezunovic et al. [36] focused on synchronized sampling, examining symmetrical components for fault identification, which can be limited to the sampling rate and loss of some of the important details, affecting its accuracy. Rahmati et al. introduced a sequential components approach, emphasizing the change in load angle [20], but it is be affected by the fault resistance which cannot be predictable.

Kumar et al. proposed a Cumulative Differential Sum procedure using K-mean clustering and weighted K-Nearest Neighbor regression [11]; as stated, this algorithm is affected by the noise and fault resistance. Singh and Sharma employed Empirical Mode Decomposition, and their algorithm overcomes the fault location impact [12], but as mentioned, it is still limited to the threshold setting which varies from network to another as in [13]. Meanwhile, Saber introduced backup protection using a phasor measuring unit (PMU) [9], despite having applied their algorithm on different scenarios but still not covering all possible cases. In addition, their algorithm required the use of a filter for the noise removal and this may cause the removal of sensitive data or features.

UI Haq et al. utilized Discrete Wavelet Transform (DWT) and a two-channel extreme learning machine [17]. Also, Chen employed unsupervised feature learning with a convolutional Sparse Autoencoder [37]. Bhowmik et al. incorporated a wavelet into a Neural Network, coupling it with Fast Fourier Transform (FFT) to extract features [38]. Also, Patel proposed TL protection using Wavelet and Artificial Neural Network (ANN) [39], while Gayathri favored Wavelet Transform over Fast Fourier Transform (DWT and FFT) for fault diagnosis [24]. Subsequently, in their work the use of the FFT faces the consequences of window limitation and absence of time. Jamil utilized Neural Networks for TL fault identification [30]. Also, Tong introduced a graph convolutional Neural Network (NN) as a novel approach [14]. Despite the fact that the aforementioned models based on deep networks have been proved to be effective in fault detection and classification, they still impose challenges such as recognition accuracy and computational complexity.

Agarwal et al. proposed fuzzy inference algorithms for fault detection [16], while A. S. et al. employed fuzzy logic plus wavelet for low computational burden fault identification [27]. Nevertheless, it encountered the challenge of recognizing information extracted from the signal and must go through the preprocessing filtration, which has to remove some significant feature and has a similar case as its predecessors [9]. However, Air et al. developed a superimposed fault detection method focusing on three-phase current and voltage signals [28,29] and resolved the problem of considering the system parameters variations. Consequently, their proposed method has a high computational cost in addition to the use of DWT, which reduces the resolution of the original signal representation.

Fan et al. adopted a unique Wavelet Transient approach based on the WT energy, distinguishing between internal and external faults [40]. They overcame the computational cost and complexity but have a long fault detection time of 27 ms. Aguilera combined distance relay with traveling current waves for competitive TL fault identification [41]. They faced the same problem of the time in addition to the threshold setting, which differ from one network to other.

Biswas proposed a differential approach based on positive sequence current for minimal computational burden [10], and although it addresses the computational burden and considered changes of variables in most networks during faults, the processing time remains relatively high and the approach did not consider noise disturbance. De Souza employed function analysis and computational intelligence [42], yet their studies lack consideration of noise; furthermore, important system variables with a direct impact on fault analysis were not accounted for.

While all the aforementioned methodologies have made valuable contributions to TL fault identification, they come with certain drawbacks. Many methods face challenges in handling noisy signals, leading to potential inaccuracies in fault detection. Moreover, some approaches may lack robustness when applied to diverse fault scenarios or may not adequately address series faults, which have been comparatively understudied.

In contrast, the proposed methodology in this work seeks to address these limitations by leveraging both wavelet and scalogram images. The combination of wavelet and scalogram images enhances the ability to capture intricate fault patterns across different frequencies and time scales, providing a more comprehensive and robust analysis. The introduction of scalogram images contributes to improved fault visualization, aiding in the identification of the small fault features that may be challenging to be recognized in traditional signal processing methods.

Furthermore, the proposed methodology has the capability to detect faults within a 1/4 cycle, offering swift and precise identification. This rapid detection time is a significant advancement, crucial for minimizing potential damage and ensuring the quick isolation of faults in the transmission line system. By combining the strengths of wavelet and scalogram images, the proposed algorithm aims to overcome the limitations of existing methods, presenting an effective solution for TL fault identification.

## 2. System Requirements and Challenges

Many aspects must be considered while developing a model for the protection of electricity transmission lines. The protection system can interpret changes in a faulty signal as normal behavior, while other times it may interpret a normal signal as a faulty one. The following are some of the difficulties associated with the protection system reliability:

1. Fault impedance.
2. Fault inception angle (FIA).
3. Compensation (series and/or shunt).
4. Other transmission factors such as loads, branches, transformers, etc.

The main aim of developing a TL protection system is that it can handle all potential changes in TL parameters without being affected by deviations and changes from all the system components. Furthermore, all systems developed so far have shortcomings which prevent them from being used as holistic protection systems for all transmission line

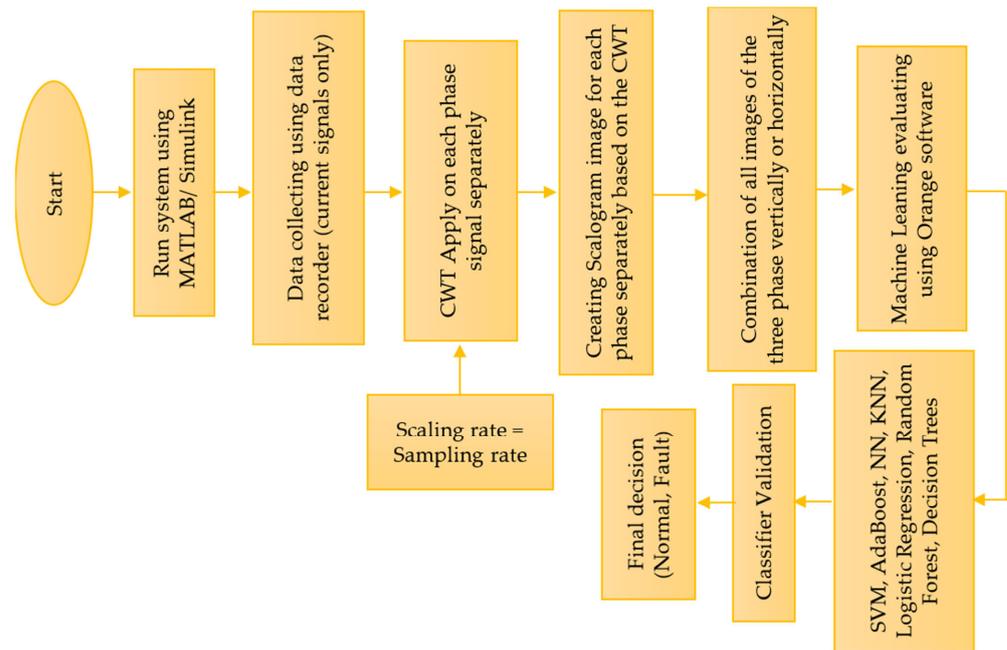
networks. The following are some of the common drawbacks in power transmission line protection systems:

- Only shunt faults are considered, while series faults are ignored. While the shunt faults have a high impact on the system, the series faults have less impact. However, both have an affect on the power system equipment life.
- Using a very simple network consisting of TL and fixed generators. Using only a simple network does not represent the real-world TL system, and the fault on such systems is not as complex as the real system. Thus, the TL that has additional components suffers their contribution to the fault as well.
- Theories are based on the TL protection to the threshold point, which differs from one network to another. This happens when the threshold is a fixed value which is different from one network to another, and may not be valuable if the system has changed by adding or removing components, load, . . .etc.
- Some theories utilize a supervised approach that requires a significant quantity of data and training. In general, increasing the number of datasets has the advantage of increasing the efficiency of these models, which means that it has been trained on most of the probabilistic scenario and vice versa. However, this is costly and requires time for training.
- Noise is a significant obstacle to the protection system as it can lead to misdiagnosis. This can be a major point in the diagnosis of signals. Therefore, not considering the noise in the fault analysis method causes a malfunction in the protection system as this noise is considered as a disturbance in the system, viz, it is a faulty signal.
- Fault inception angle (FIA) has an impact on the TL protection system. Without considering this factor FIA in any model lead to be a weak point for the model because the fault may occur in any FIA. That means, the future prediction results will be improper and unreliable.
- Computational cost which can be time consuming. Taking data from TL both ends costs resources and time for the fault diagnosis due to the fact that collecting data from two sides of a long transmission line needs a communication system, data preprocess, and devices besides the time to analyze.

Therefore, regardless of the system's structure or composition, a worthwhile objective is to develop an optimum approach that can overcome all these difficulties and imperfections, while still being very reliable in fault detection under all circumstances.

### 3. The Proposed Methodology

In this study, the methodology for detecting faults in transmission lines depends on a comprehensive analysis employing wavelet and scalogram techniques. The rationale behind this approach lies in the inherent capacity of Wavelet Transforms to decompose signals into various frequency components, allowing for an enhanced understanding of the signal characteristics associated with different fault conditions. The homogeneous integration of scalogram analysis further enriches the proposed fault detection capabilities by providing a time-frequency representation of the signals. Adopting a multi-resolution analysis strategy, which aimed to leverage the strengths of both wavelet and scalogram analyses, can achieve a robust and accurate detection system for identifying faults in transmission lines. The following sections elaborate on the specific steps involved in data collection, pre-processing, wavelet analysis, scalogram analysis, and the development of a fault detection algorithm to realize this methodology. Figure 1 below shows the flowchart of the whole process of the system as it was implemented.



**Figure 1.** Flowchart for fault detection process.

3.1. Data Collection

The data utilized in this study for the purpose of fault detection in transmission lines were generated by running a complex network simulation on MATLAB/Simulink (2023b). The dataset comprises time-domain phase current signals collected from one side of the network. This approach was adopted to mitigate the cost associated with using dual-side data recorders, as suggested in [43,44]. The data include recordings of both normal operating conditions and instances of known faults. The transmission line data are characterized by their high time resolution, enabling the capture of the smallest changes or deviations in the electrical signals. The dataset provides a comprehensive representation, including frequency, time, and amplitude information. The data were sampled at a rate of 10 kHz, with a duration of 0.2 s. The data collected were 4752 images for each type of noise (Ideal, 10 dB, 20 dB and 30 dB). The dataset encompasses all fault scenarios as shown in Table 1 below. This diversity in fault scenarios ensures a thorough evaluation of the proposed fault detection methodology under various conditions. The inclusion of both normal and faulty operating conditions in the dataset contributes to the robustness of the analysis.

**Table 1.** System parameters under different scenarios.

System Condition	Parameters
Shunt fault	AG, BG, CG, AB, AC, BC, ABG, ACG, BCG, ABCG and NORMAL
Series fault	One line open, two lines open
Noise level	Ideal, 10, 20 and 30 dB
Fault inception angle	30, 60, 90, 180, 270, 360
Fault location	20, 30, 40, 50, 75, 100, 150, 200, 280
Fault resistance	0.001, 0.005, 1, 10, 50, 75, 100, 200

3.2. Continuous Wavelet-Based Algorithm

In this paper, we propose a novel approach in the field of transmission lines protection by leveraging the scale of the Wavelet Transform to be as the same as the sampling rate, which results in the capture of most of the changes in the signal at the time of signal sampling. The wavelets used create a two-dimensional scalogram image [45–48], which in turn is used to identify the abnormal behavior of the current passing through the

transmission lines in a very short time. The application of the DSP theory arose because of all the aberrant changes that can occur in the transmission network system, which translate into a change in the current or voltage signals. It was also found that analyzing the signal spectrum provides a lot of information about the system's health and changes. As a result, the Fourier Transform (FT or even FFT) has been employed, which has shown to be effective in a variety of applications [49], but has the following associated shortcomings:

1. Time factor: Time does not exist for the Fourier transform, which makes it difficult to apply this theory to power systems that rely on signals traveling through time [49].
2. Window limitation cannot be employed when the signal changes in a very short time or even slightly, such as when the signal passes through a transitory period [50].

Fourier Transform

$$F(\omega) = \int_{-\infty}^{\infty} f(t)e^{-j\omega t} dt \quad (1)$$

Fast Fourier Transform

$$F_k = \sum_{n=0}^{N-1} x_n \cdot e^{-\frac{j2\pi kn}{N}} \quad (2)$$

where  $k$  and  $n$  are integers related to the number of samples.

Dennis Gabor developed a novel approach in 1946 to remedy the FFT shortcomings mentioned above. Using the method of signal analysis through the tripartite representation of the signals addressed the time problem [49]; meanwhile, for the window limitation issue, he proposed the use of several windows rather than a single window and STFT, i.e.,

1. Time: it depicts the waveform with three signal spectrum fields (time, magnitude, and frequency).
2. Window: the segmentation of the signal is treated as if it were a stationary signal. Consequently, STFT has a pre-defined restricted multi-window configuration.

$$STFT\{f(t)\}(\tau, \omega) = F(\tau, \omega) = \int_{-\infty}^{\infty} f(t) w(t - \tau) e^{-j\omega t} dt \quad (3)$$

Even though STFT is capable, to some extent, of overcoming prior hurdles with a decent outcome, it still has shortcomings for specific applications, such as power system signal analysis, which can be summarized as follows:

1. The window: once specified, it cannot be altered.
2. Resolution pinpoint: this indicates that the window is directly proportional to frequency resolution and inversely proportional to time, and vice versa. This means that any component can result in either excellent frequency resolution or time resolution, but not both.  $W_d \propto F/T$ .
3. Time interval and frequency: this is regarded as the most difficult and demanding aspect of using STFT in power system analysis, particularly for transmission line protection.

In order to address the aforementioned drawbacks, wavelets were introduced as alternatives to the previous algorithms in the signal analysis [36,40,49,50] (see equation below). The Wavelet Transform has generated a significant deal of interest and is now widely used in the fields of image and speech processing.

$$CWT(a, b) = \langle f, \psi_{a,b} \rangle = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \cdot \psi_{a,b}^* \left( \frac{t-b}{a} \right) dt \quad (4)$$

$a, b \in \mathbb{R}$  &  $\psi_{a,b}$  is the wavelet,  $\psi_{a,b}^*$  represents the complex conjugate of the mother wavelet.

- $a$  (binary dilation or scale parameter): can compress or stretch the wavelet signal [51].
- $b$  (binary position or translation parameter): used for shifting the wavelet signal over the original signal.

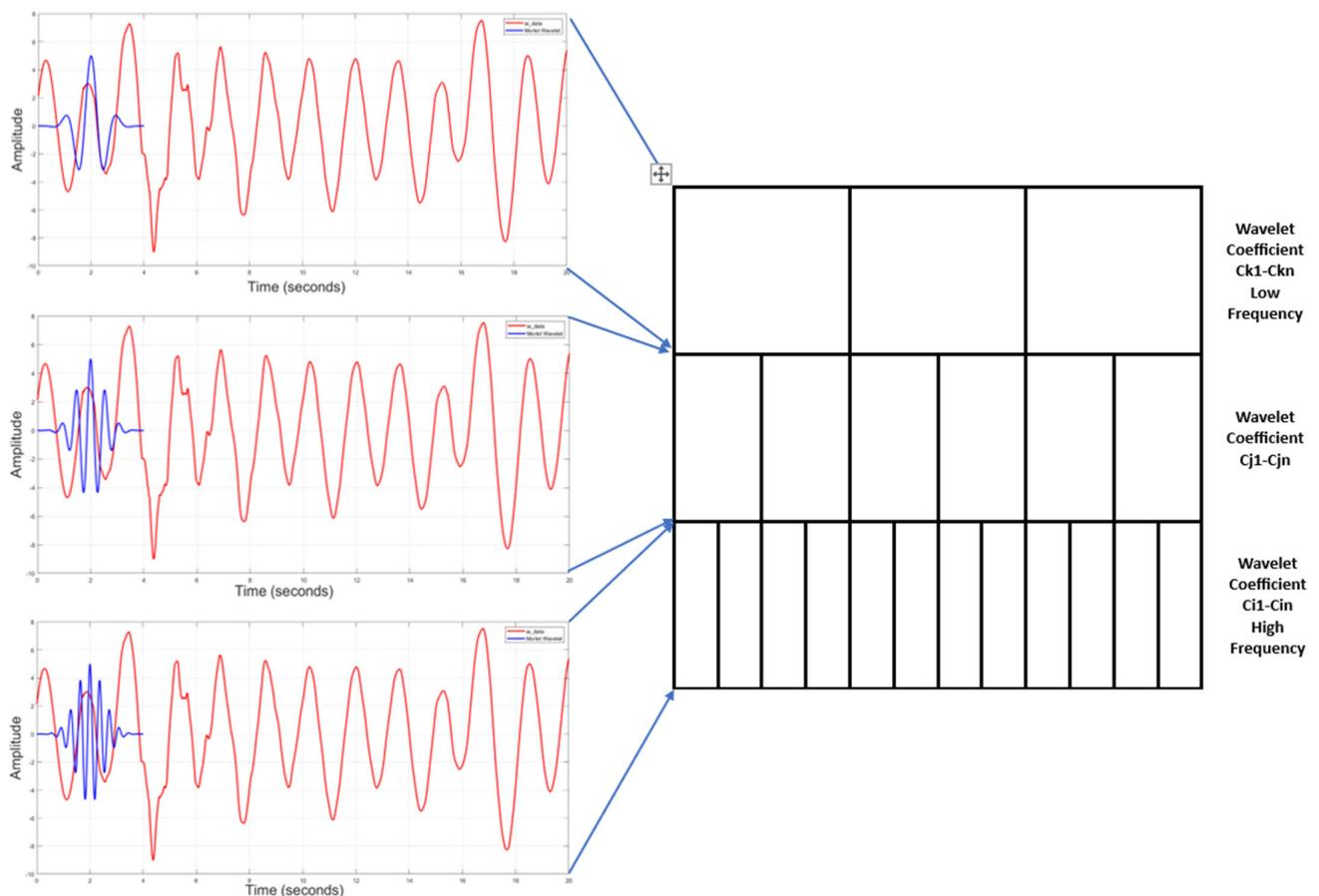
It is worth mentioning that with Fourier transforms, signals are represented by waves of different frequencies, while with Wavelet Transforms, signals are expressed by wavelets of different scales and positions.

In this approach, the Wavelet Transform is used to detect faults in power transmission lines. To test the integrity and reliability of this method, several tests with varying fault location, fault inception angle, and fault resistance were used. Also, tests of validity on complicated systems with additional variable or fixed loads, compensators, transformers, and other components were conducted.

The performance of the present method with general and complex systems compared to existing methods suggests that the proposed methodology constitutes a step-change in power transmission lines' fault detection algorithms. The detailed algorithm is as follows:

1. Collect data from sending end.
2. Sampling data collected.
3. Applying wavelet for the signals' feature extraction.
4. Converting results in a 2D visualizing scalogram image.

Note that in [36], it is mentioned that Daubechies' wavelet group is one of the most often used Wavelet Transforms in the field for power system transient signal analysis for identifying short lifespans and rapidly decaying faults. However, with the proposed method, it was found that all wavelets' families produces similar results (i.e., the wavelet choice is secondary). Figure 2 below shows the convolution of the faulted phase current with the wavelet (morlet) and the output of this process in terms of coefficients.



**Figure 2.** Transforming phase current signal into wavelet coefficient using (morlet) at different scales (i,j,k).

### 3.3. Scalogram Analysis

Scalogram analysis serves as a vital component complementing wavelet analysis in the proposed fault detection methodology for power transmission lines. While wavelet analysis efficiently extracts features from signals, scalogram analysis addresses certain limitations inherent in Wavelet Transforms.

#### 3.3.1. Wavelet Transform Limitations

The Wavelet Transform, while powerful, encounters challenges in capturing transient events with high precision due to its fixed time–frequency resolution. Additionally, the choice of the mother wavelet may impact its effectiveness across diverse signal patterns. These limitations can prevent the accurate identification of fault signatures, especially in scenarios where fault events exhibit rapid changes in frequency and amplitude.

#### 3.3.2. Role of Scalogram Analysis

Scalogram analysis overcomes these limitations by providing a time–frequency representation of the signal in a visually intuitive manner. Instead of relying solely on the wavelet coefficients, scalograms offer a spectrogram-like visualization that highlights frequency variations across time. This graphical representation enhances the ability to recognize slight changes associated with faults, even during brief intervals.

#### 3.3.3. Scalogram Generation and Interpretation

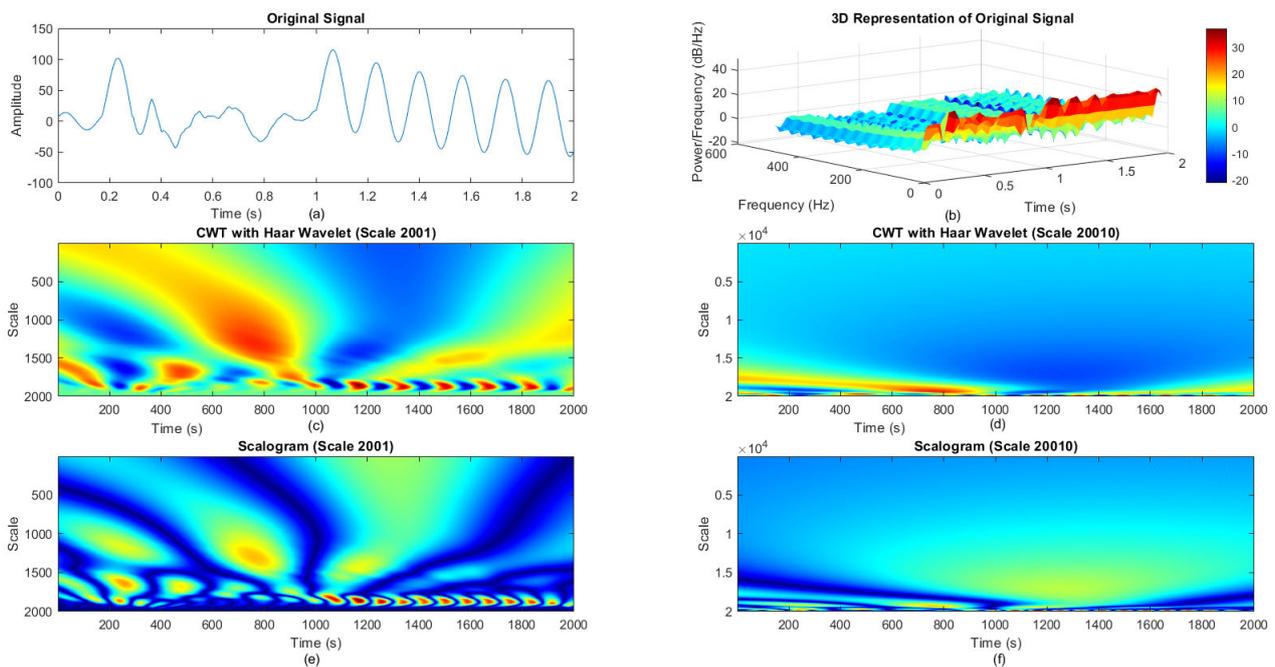
The scalograms were generated by applying the Continuous Wavelet Transform (CWT) to the collected data. The CWT, with its variable time–frequency resolution, captures the complicated details of the signal across different scales. The resulting scalogram images show the development of signal frequencies over time, presenting a comprehensive view of the signal characteristics. Interpretation of scalograms involves a qualitative analysis of the visual patterns. Abnormal behavior, such as shifts in frequency or the emergence of distinct features, are indicative of potential faults. The utilization of scalograms alongside wavelet analysis enhances the fault detection process by providing a supplementary visual tool that facilitates the identification of fault-related patterns in a manner more robust to transient events.

The scalogram is not defined by a single equation but is derived from the Continuous Wavelet Transform (CWT). The CWT is expressed mathematically by Equation (4) above, while the scalogram is essentially a plot of the magnitude of the CWT coefficients as a function of scale and time. Mathematically, it can be represented as

$$\text{Scalogram}(a, b) = |\text{CWT}(a, b)| \quad (5)$$

This magnitude represents the strength or energy of the signal at each scale and time instant. In practice, the scalogram is often visualized using a spectrogram-like plot, where the  $x$ -axis represents time, the  $y$ -axis represents scale, and the color intensity or contour lines represent the magnitude of the CWT coefficients. Figure 3 below illustrates the way that the signal is presented using the scalogram transforming based on the Wavelet Transformation.

Moreover, scale plays a vital role in forming of the image. It is clear from Figure 3 that scale can diminish the details of the scalogram image when it is higher than required. Therefore, it has been selected to be the same as the sampling rate. This means each value has a representation on the opposing side.



**Figure 3.** (a) Original signal. (b) 3D representation of the original signal. (c) CWT scale 2000. (d) CWT scale 20,000. (e) Scalogram for CWT scale 2000. (f) Scalogram for CWT scale 20,000.

### 3.3.4. Machine Learning Integration

To rigorously validate and demonstrate the robustness of the combination of wavelet and scalogram fault detection algorithm, our method employs a comprehensive machine learning framework using the Orange data mining software (V3.34.0). This framework utilizes various well-established machine learning classifiers, including Support Vector Machines (SVM), AdaBoost, Neural Networks (NN), k-Nearest Neighbors (KNN), Logistic Regression, Random Forest, and Decision Tree.

In this study, each classifier was individually trained on the features extracted through the proposed wavelet and scalogram analyses. This training process involved extensive datasets encompassing diverse fault scenarios, fault locations, inception angles, and fault resistances, as well as non-fault conditions. Furthermore, the classifiers were trained and tested separately on the features obtained from images created by the combination of wavelet and scalogram. This completed evaluation enabled the assessment of the collective contributions of wavelet and scalogram analyses to fault detection accuracy.

The classification results from SVM, AdaBoost, NN, KNN, Logistic Regression, Random Forest, and Decision Trees served as quantitative benchmarks for the effectiveness of the research methodology. The incorporation of diverse classifiers facilitated a thorough analysis of the algorithm's performance across different fault scenarios, contributing to its adaptability and generalizability. The utilization of well-established classifiers within Orange, coupled with the training and testing, substantiates the reliability and applicability of the combined wavelet and scalogram fault detection methodology.

### 3.3.5. Validation and Performance Metrics

The proposed methodology's effectiveness was rigorously validated through a multi-faceted approach. Simulated data from MATLAB Simulink simulations, encompassing a wide range of fault scenarios and system complexities, formed a foundational element of the validation strategy. Additionally, real-world datasets with known faults were employed to ensure the applicability of the proposed fault detection system in practical scenarios. To assess the accuracy of the proposed fault detection system, and based on Figure 4, it utilized a complete set of performance metrics. These metrics included the following.

## 1. Sensitivity:

The ability of the system to correctly identify true positive instances of faults.

$$\text{Sensitivity} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \quad (6)$$

## 2. Specificity:

The capacity of the system to accurately identify true negative instances of normal operation.

$$\text{Specificity} = \frac{\text{True Negatives}}{\text{True Negatives} + \text{False Positives}} \quad (7)$$

## 3. Precision:

The proportion of correctly identified faults among all instances classified as faults, measuring the system's positive predictive value.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \quad (8)$$

## 4. Recall:

The ratio of correctly identified faults to the total number of actual faults, gauging the system's ability to capture all instances of true positive faults.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negative}} \quad (9)$$

## 5. F1 Score

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (10)$$

		Actual value	
		Positive (1)	Negative (0)
Predicted Value	Positive (1)	True Positive	False Positive
	Negative (0)	False Negative	True Negative

**Figure 4.** Confusion matrix of the testing data.

These metrics collectively provide a comprehensive evaluation of the fault detection system's performance, offering insights into its accuracy, robustness, and reliability under diverse conditions. The combination of simulated and real-world datasets, along with the application of rigorous performance metrics, ensures the validity and generalizability of the proposed methodology for power transmission line fault detection.

### 3.3.6. Experimental Setup

The experimental setup embraced a multifaceted approach to data analysis within the Orange software, complementing the versatile data collection capabilities of MAT-

LAB/Simulink. Three distinct strategies were employed for data analysis, each contributing unique perspectives to the fault detection methodology.

#### 1. Classification based on the image features:

An alternate strategy involved the direct analysis of extracted data features without image embedding. Orange provided a comprehensive environment for feature analysis and classifier evaluation, allowing for the training and testing of a diverse set of classifiers on the raw feature data. This approach highlighted the significance of individual features in fault detection.

#### 2. Classification based on high ranked image features:

To enhance efficiency, a third approach involved data reduction and feature selection. Orange facilitated the extraction of the highest-ranked features from images, optimizing computational resources. Subsequently, various classifiers were applied to this reduced feature set, providing insight into the most influential factors for fault detection.

In conjunction with the algorithms mentioned earlier, this expanded experimental setup allowed for us to explore the fault detection methodology from multiple angles. The seamless integration of MATLAB/Simulink and Orange empowered a comprehensive evaluation across simulated and real-world datasets, emphasizing the adaptability and robustness of this approach in diverse scenarios. The inclusion of different data analysis strategies provided a nuanced understanding of the methodology's performance, fostering a more informed and versatile fault detection framework.

## 4. Simulation Results and Discussion

### 4.1. Introduction to Results and Discussion

The transmission network is designed in MATLAB/Simulink to simulate various faults. On one end, there are six 350 MVA 13.8 KV generating units, while on the other end, there is one 30,000 MVA 735 KV generating unit. Two nonlinear and two linear loads are coupled with these two generators in a transmission network. There are two reactive loads, each with a capacity of 330 MVAR lagging load and active loads of 100 MW and 250 MW. On one end, there are six 350 MVA, 13.8/735 KV (two windings) transforming units, while on the other end, there is one 300 MVA, 735/230 KV (three windings) transforming units as shown in Figure 5, [32].

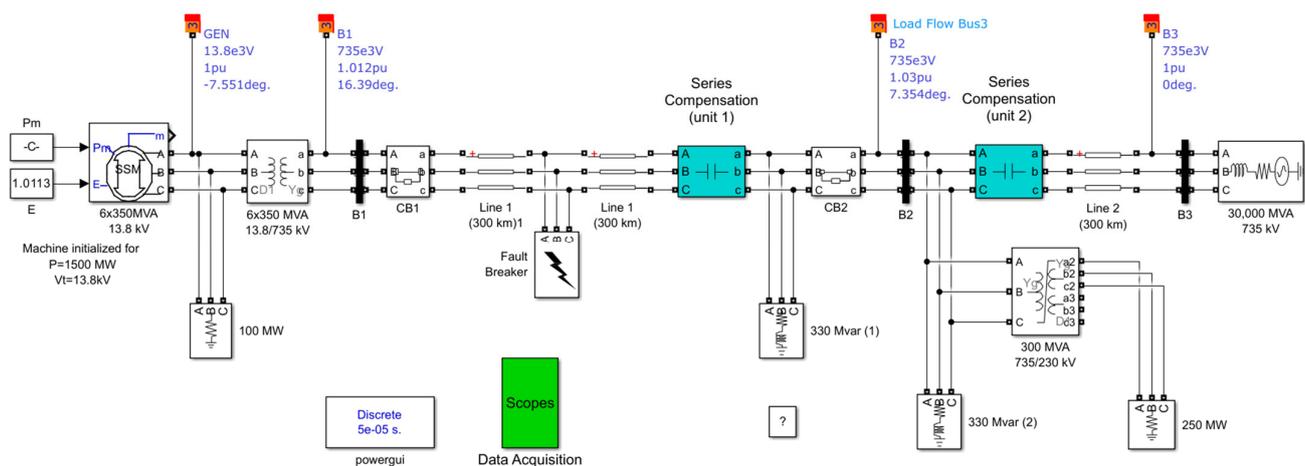
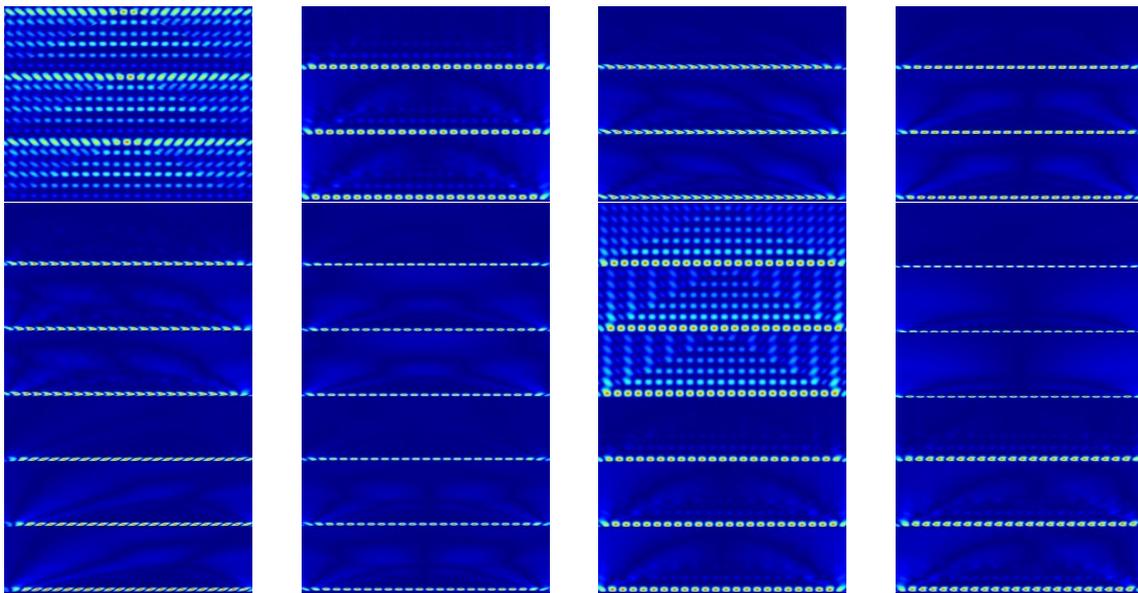


Figure 5. Three-phase series compensating network.

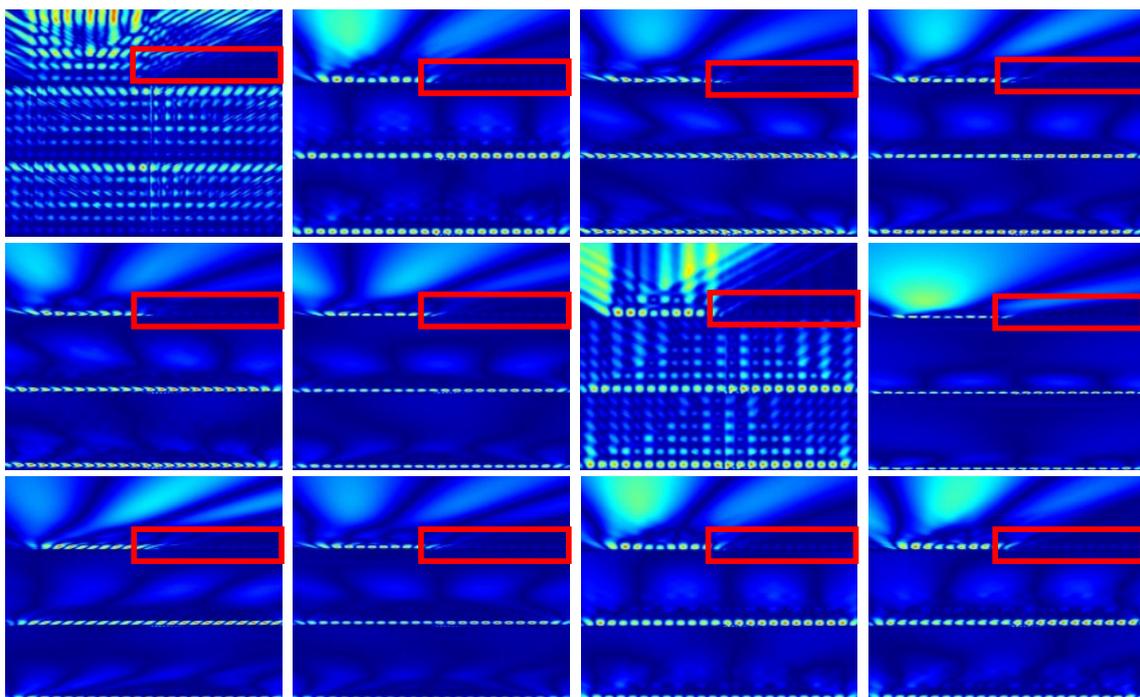
The Wavelet Transforms need inputs in the form of samples to permit the Wavelet Transforms to be transformed into a scalogram image. Three-phase current signals were the input to the system for different scenarios, which are shown in Table 1. Figures 6–8 show the outcome from using different types of wavelets transforms. The red boxes show the start change in the signal behavior.

**Table 2.** Wavelet families are used for fault detection with their specific level.

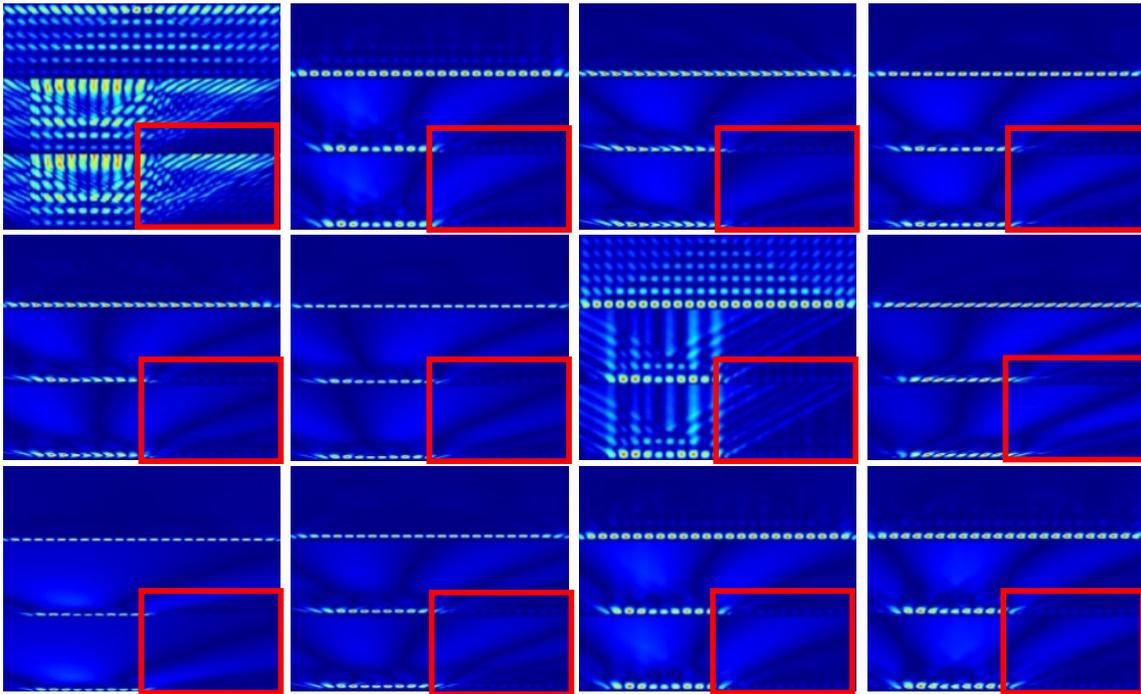
'bior' Biorthogonal wavelets-3.1	'coif' Coiflets-2	'db' Daubechies wavelets-7	'dmey' Discrete approximation of Meyer wavelet-14
'fk' Fejér-Korovkin filters-14	'gaus' Gaussian wavelets-7	'haar' Haar wavelet-	'mexh' Mexican hat wavelet (also known as Ricker wavelet)-
'meyr' Meyer wavelet-	'morl' Morlet wavelet-	'rbio' Reverse biorthogonal wavelets-4.4	'sym' Symlets-5



**Figure 6.** Normal work for different wavelet families and levels as shown in Table 2.



**Figure 7.** Single line to ground AG fault for different wavelet families.

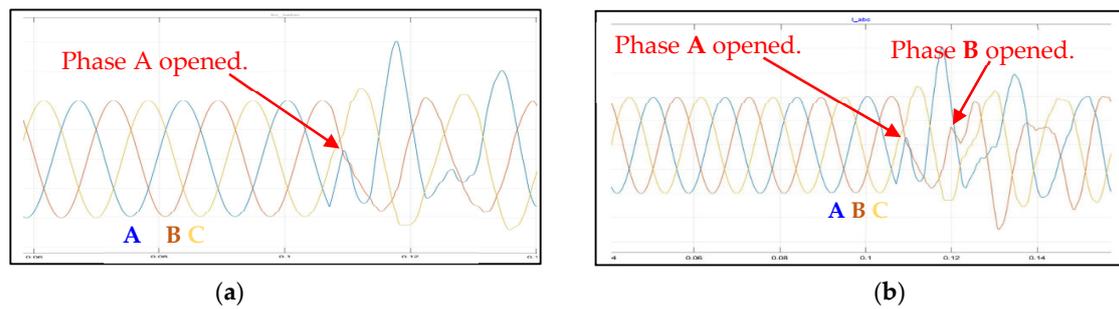


**Figure 8.** Double line BC g fault for different wavelet families.

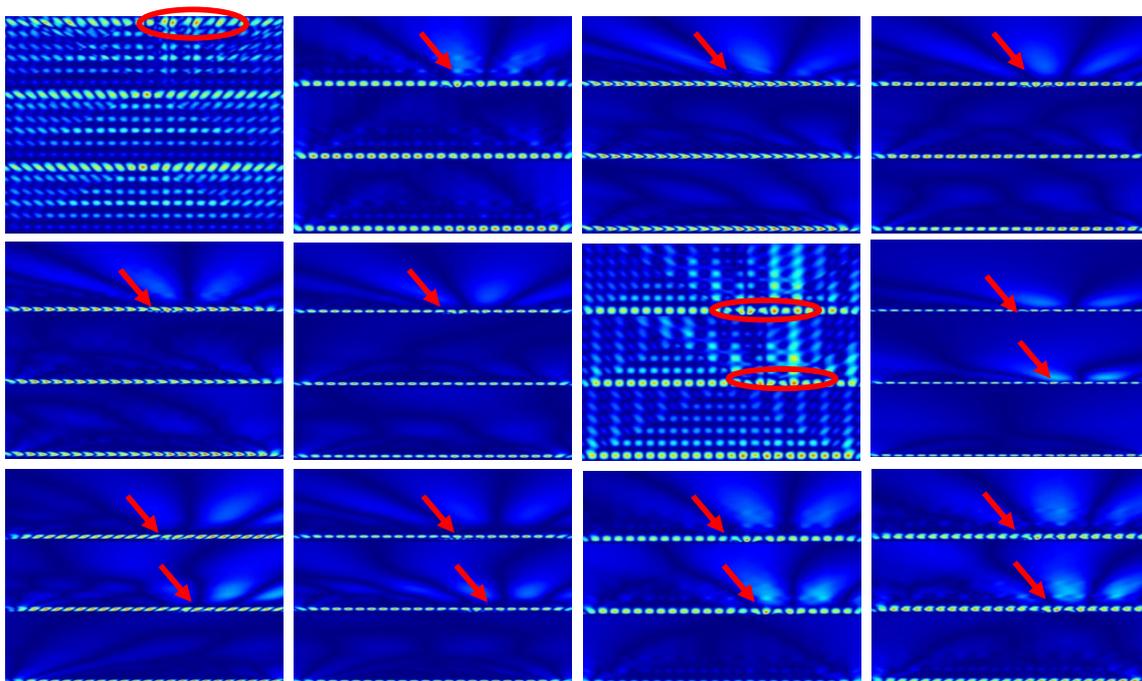
Faults are detected within a very short of time  $1/4$  cycle. Table 2 represents all wavelet families used for fault detection with their specific levels.

It is worth mentioning that a decision process based on a very short time-window is not always wise. However, most TL protection systems aim to find faults as fast as possible, because a significant delay can cause a substantial negative impact. The decision-making process must also consider the fact that the time factor is also critical for distinguishing between real faults and short-term minor disturbances that do not affect the system.

Most previous researchers overlooked the fault which happens when one or two lines are open as in Figure 9a,b, and as shown in Figure 10, (1–6) and (7–12), respectively, which is the result of a system flaw. Thus, the signal cut-off, as shown in Figure 9, obviously, is a change at a specific time, which the Fast Fourier Transform is unable to distinguish, because the FFT represents the signal value and frequency without mentioning time. This feature distinguishes Wavelet Transform from others and its ability to determine time related to the frequency and magnitude changes. From the results, it can be clearly seen that this approach leads to good results. The methodology permits detecting faults by displaying the signal changes as a two-dimensional image, from which one can clearly distinguish between normal and abnormal states of the system. It is a well acknowledged fact that with other methods, extra variables such as noise, fault resistance, fault inception angle, and fault location have an impact on the fault detection algorithm. However, the results show that the changes that can occur in the system due to faults do not affect the ability of the proposed method to still accurately identify the true faults. This approach has been tested and validated on a circuit that replicates reality and contains most of the elements found in realistic power systems.



**Figure 9.** Three-phase current signals. (a) One-line opened (line A). (b) Two-lines opened (lines A and B).

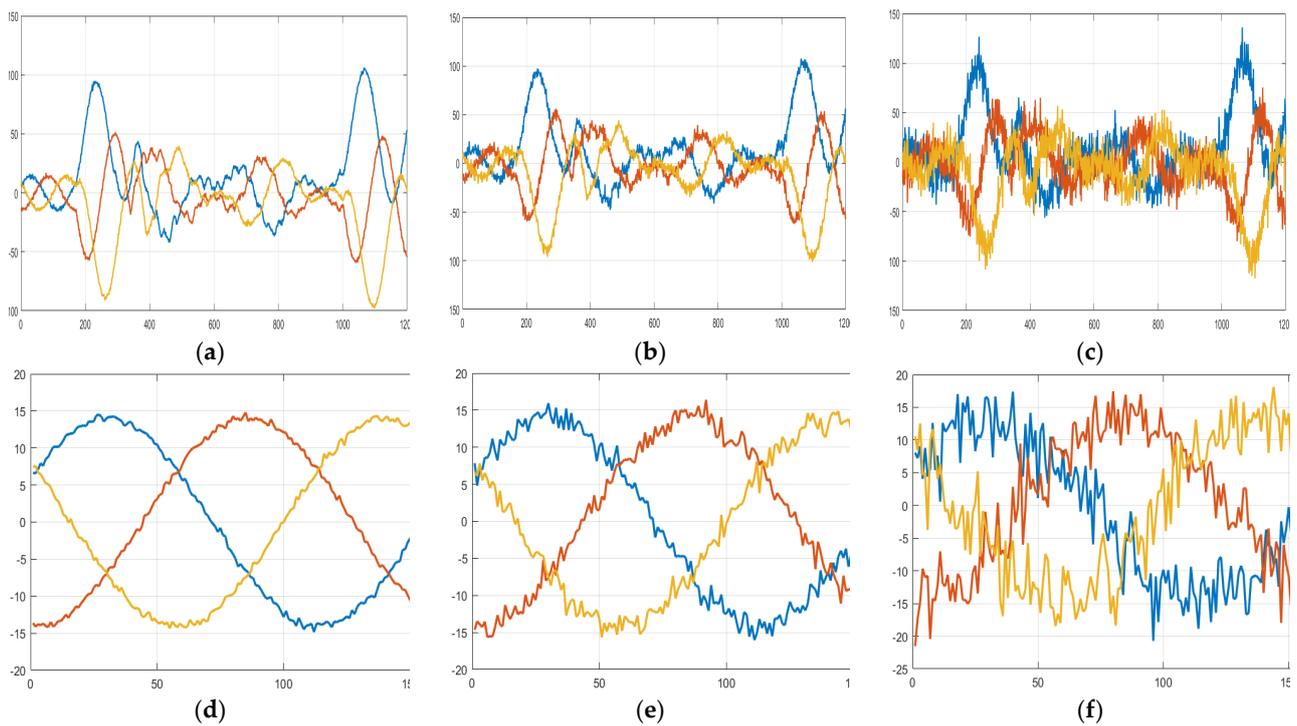


**Figure 10.** When one line (1–6 images) or two lines (7–12 images) opened.

#### 4.2. Effect of Noise

The proposed method showcases a high tolerance to noise, with negligible impact on its performance. The accuracy and effectiveness of fault detection persist even in the presence of varying noise levels. Unlike traditional methods that may struggle with signal distortion caused by noise, the proposed algorithm leverages advanced signal-processing techniques, ensuring reliable fault detection. This robustness is particularly advantageous in practical applications where noise is an inherent aspect of power system signals. Figure 11 illustrates the effect of the noise on the signal in both faulted and non-fault scenarios.

The proposed algorithm went through different training, validation, and testing under varying noise levels, demonstrating exceptional accuracy rates of 100% across three distinct AI settings. These high results are clearly illustrated in the figures below, highlighting the robustness and efficacy of the algorithm in fault detection under diverse conditions. Figure 12 shows the classification accuracy and evaluation metrics for the proposed methodology.



**Figure 11.** (a–c) Three phase current signals while fault ABC g occurred (30, 20, and 10 dB) noise were added, respectively; (d–f) three phase currents with No-Fault condition, but (30 dB, 20 dB, and 10 dB) noise were added, respectively.

Evaluation results for target (None, show average over classes)					
Model	AUC	CA	F1	Precision	Recall
Tree (2)	1.000	1.000	1.000	1.000	1.000
SVM (1)	1.000	1.000	1.000	1.000	1.000
SGD	1.000	1.000	1.000	1.000	1.000
Neural Network	1.000	1.000	1.000	1.000	1.000
Logistic Regression (1)	1.000	1.000	1.000	1.000	1.000

(a)

Evaluation results for target (None, show average over classes)					
Model	AUC	CA	F1	Precision	Recall
Tree (2)	0.999	1.000	1.000	1.000	1.000
SVM (1)	1.000	1.000	1.000	1.000	1.000
SGD	1.000	1.000	1.000	1.000	1.000
Neural Network	1.000	1.000	1.000	1.000	1.000
Logistic Regression (1)	1.000	1.000	1.000	1.000	1.000

(b)

Evaluation results for target (None, show average over classes)					
Model	AUC	CA	F1	Precision	Recall
Tree (2)	0.999	1.000	1.000	1.000	1.000
SVM (1)	1.000	1.000	1.000	1.000	1.000
SGD	1.000	1.000	1.000	1.000	1.000
Neural Network	1.000	1.000	1.000	1.000	1.000
Logistic Regression (1)	1.000	1.000	1.000	1.000	1.000

(c)

**Figure 12.** Classification accuracy and evaluation metrics (a) without noise and with 30 dB noise, (b) 20 dB noise, and (c) 10 dB noise.

### 4.3. Discussion of Results

In interpreting the results obtained from the comprehensive evaluation, it is crucial to contextualize them within the broader framework of the research objectives. The primary goal of this study was to introduce a fault detection method that not only overcomes traditional challenges but excels under extreme conditions, particularly in the presence of varying noise levels. The proposed algorithm’s success in achieving 100% accuracy across diverse scenarios underscores its alignment with these objectives. Table 3 illustrates the performance of the proposed methodology.

The proposed method’s achievement of optimal accuracy for fault detection offers a level of precision that is vital for maintaining the integrity and stability of power networks. Comparing the performance of the proposed method with other algorithms further emphasizes its superiority. The testing, involving several machine learning algorithms, highlights the proposed algorithm’s exceptional capability to discern faults. This is particularly noteworthy when examining its performance under different noise levels in contrast to conventional practices where researchers often avoid testing under 10 dB noise level due to

the significant challenges it poses. This deliberate choice to subject the proposed algorithm to this noise level was intentionally tested for further investigation. The proposed method not only meets the challenges posed by lower dB values but excels, proving its resilience and adaptability. The metrics used provide a quantitative basis for evaluating the proposed algorithm's superiority in fault identification. All algorithms achieved high accuracy in fault detection 100%.

**Table 3.** Performance metrics for the proposed fault detection methodology.

Classifier Type	According to Image Embedding Inputs		According to Image Features		According to 250 High Ranked Image Features	
	Accuracy %		Accuracy %		Accuracy %	
	Ideal	With Noise 10, 20, and 30 dB	Ideal	With Noise 10, 20, and 30 dB	Ideal	With Noise 10, 20, and 30 dB
Logistic regression	100	100	100	100	100	100
SVM	100	100	100	100	100	100
Random forest	100	100	100	100	100	100
Neural Network	100	100	100	100	100	100
kNN	100	100	100	100	100	100
AdaBoost	100	100				
Decision Tree	100	100				

## 5. Conclusions

In conclusion, this research has introduced a significant contribution to fault detection methods for power transmission line protection systems, leveraging an innovative application of Wavelet Transforms and scalogram theory. Comprehensive validation through various network simulations has revealed the method's very-high performance across a spectrum of challenges. A notable aspect of our study involves the introduction of noise at different levels (10, 20, and 30 dB) during testing. Despite these noise levels, the proposed method consistently demonstrated robust fault detection capabilities. The incorporation of three fundamental signal aspects—value, frequency, and time—via Wavelet Transforms combined with the scalogram theory represents a superior approach. By examining the small details of the signal, this technique makes it possible to determine fault-detection characteristics among a variety of the signals' features that indicate no faults. The unique presentation of outcomes in an image format further distinguishes the proposed method, providing a clear and concise means of fault identification within a short time frame.

The demonstrated effectiveness of the approach in achieving 100% accuracy is a testament to its significance in the field of fault detection systems. Unlike conventional methods, this approach overcomes traditional challenges, offering a robust and reliable solution that remains unaffected by the complexity of the power system that is being studied. The adaptability and persistence of the proposed method, validated through extensive testing, mark it as a valuable tool for the field of transmission line systems. This method proves its potential positive impact across the entire industry.

**Author Contributions:** Conceptualization, A.S.A. and M.A.; Software, A.S.A.; Validation, A.S.A.; Investigation, A.A.M.; Writing—original draft, A.S.A.; Writing—review & editing, M.A.; Supervision, M.A. and A.A. All authors have read and agreed to the published version of the manuscript.

**Funding:** The first two authors, A.S. Altaie and A.A. Majeed, have received a Ph.D. scholarship from the Iraqi Ministry of Electricity. M. Abderrahim receives funding for his research activities from Ro-boCity2030-DIH-CM, Madrid Robotics Digital Innovation Hub, S2018/NMT-4331, funded by "The Community of Madrid and the European Social Funds", and through the Strategic Action on Intelligent Robotic Systems and Automation 2012/00605/003 funded by the University Carlos III of Madrid.

**Data Availability Statement:** Data will be available upon request.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. Anderson, P.M. *Power System Protection*; IEEE Press Power Engineering Series; McGraw-Hill: New York, NY, USA, 1999; ISBN 978-0-7803-3427-4.
2. Rathore, B.; Mahela, O.P.; Khan, B.; Padmanaban, S. Protection Scheme Using Wavelet-Alienation-Neural Technique for UPFC Compensated Transmission Line. *IEEE Access* **2021**, *9*, 13737–13753. [[CrossRef](#)]
3. Paul, M.; Debnath, S. Wavelet Based Single Ended Scheme for High Impedance Fault Classification in Transmission Lines. In Proceedings of the 2020 International Conference on Smart Technologies in Computing, Electrical and Electronics, Virtual, 9–10 October 2020.
4. Fahim, S.R.; Das, S.K.; Sarker, Y.; Sheikh, R.I.; Sarker, S.K.; Datta, D. A Novel Wavelet Aided Probabilistic Generative Model for Fault Detection and Classification of High Voltage Transmission Line. In Proceedings of the 2020 2nd International Conference on Smart Power & Internet Energy Systems (SPIES), Bangkok, Thailand, 15–18 September 2020; pp. 94–99.
5. Lozada, F.I.; Quilumba, F.L.; Pérez, F.E. Detección y Clasificación de Fallas En Líneas de Transmisión Utilizando Transformada Wavelet y Máquinas de Soporte Vectorial. *Rev. Técnica Energía* **2018**, *14*, 151–158. [[CrossRef](#)]
6. Mohanty, S.K.; Karn, A.; Banerjee, S. Decision Tree Supported Distance Relay for Fault Detection and Classification in a Series Compensated Line. In Proceedings of the 2020 IEEE International Conference on Power Electronics, Smart Grid and Renewable Energy (PESGRE2020), Cochin, India, 2–4 January 2020; pp. 1–6.
7. Alashter, M.A.; Mrehel, O.G.; Shamekh, A.S. Design and Evaluation a Distance Relay Model Based on Artificial Neural Networks (ANN). In Proceedings of the 2020 6th IEEE International Energy Conference (ENERGYCon), Gammarth, Tunis, Tunisia, 28 September–1 October 2020; pp. 685–690.
8. Hida, S.; Pradhan, V.; Naidu, O.D.; Cheriyan, E.P. A Critical Review of Distance Relaying Techniques under Power Swing Condition. In Proceedings of the 2019 IEEE PES GTD Grand International Conference and Exposition Asia (GTD Asia), Bangkok, Thailand, 19–23 March 2019; pp. 500–505.
9. Saber, A.; Emam, A.; Elghazaly, H. A Backup Protection Technique for Three-Terminal Multisection Compound Transmission Lines. *IEEE Trans. Smart Grid* **2018**, *9*, 5653–5663. [[CrossRef](#)]
10. Biswas, S.; Nayak, P.K. A Fault Detection and Classification Scheme for Unified Power Flow Controller Compensated Transmission Lines Connecting Wind Farms. *IEEE Syst. J.* **2021**, *15*, 297–306. [[CrossRef](#)]
11. Gangwar, A.K.; Mahela, O.P.; Rathore, B.; Khan, B.; Alhelou, H.H.; Siano, P. A Novel  $k$ -Means Clustering and Weighted  $k$ -NN-Regression-Based Fast Transmission Line Protection. *IEEE Trans. Ind. Inform.* **2021**, *17*, 6034–6043. [[CrossRef](#)]
12. Singh, B.; Mahela, O.P.; Manglani, T. Detection and Classification of Transmission Line Faults Using Empirical Mode Decomposition and Rule Based Decision Tree Based Algorithm. In Proceedings of the 2018 IEEE 8th Power India International Conference (PIICON), Kurukshetra, India, 10–12 December 2018; pp. 1–6.
13. Sharma, G.; Mahela, O.P.; Kumar, M.; Kumar, N. Detection and Classification of Transmission Line Faults Using Stockwell Transform and Rule Based Decision Tree. In Proceedings of the 2018 International Conference on Smart Electric Drives and Power System (ICSEDPS), Nagpur, India, 12–13 June 2018; pp. 1–5.
14. Tong, H.; Qiu, R.C.; Zhang, D.; Yang, H.; Ding, Q.; Shi, X. Detection and Classification of Transmission Line Transient Faults Based on Graph Convolutional Neural Network. *CSEE J. Power Energy Syst.* **2021**, *7*, 456–471. [[CrossRef](#)]
15. Swain, K.B.; Mahato, S.S.; Cherukuri, M. Expedient Situational Awareness-Based Transmission Line Fault Classification and Prediction Using Synchronized Phasor Measurements. *IEEE Access* **2019**, *7*, 168187–168200. [[CrossRef](#)]
16. Agarwal, S.; Swetapadma, A.; Panigrahi, C.; Dasgupta, A. Fault Analysis Method of Integrated High Voltage Direct Current Transmission Lines for Onshore Wind Farm. *J. Mod. Power Syst. Clean Energy* **2019**, *7*, 621–632. [[CrossRef](#)]
17. Haq, E.U.; Jianjun, H.; Li, K.; Ahmad, F.; Banjerdpongchai, D.; Zhang, T. Improved Performance of Detection and Classification of 3-Phase Transmission Line Faults Based on Discrete Wavelet Transform and Double-Channel Extreme Learning Machine. *Electr. Eng.* **2021**, *103*, 953–963. [[CrossRef](#)]
18. Pan, P.; Mandal, R.K.; Akanda, M.R.R. Fault Classification with Convolutional Neural Networks for Microgrid Systems. *Int. Trans. Electr. Energy Syst.* **2022**, *2022*, 8431450. [[CrossRef](#)]
19. Dudhe, N.S.; Waghmare, D.B. Application of Wavelet Transform in Power System Analysis and Protection. *Int. J. Eng. Res.* **2017**, *6*, 889–892. [[CrossRef](#)]
20. Rahmati, A.; Adhami, R. A Fault Detection and Classification Technique Based on Sequential Components. *IEEE Trans. Ind. Appl.* **2014**, *50*, 8. [[CrossRef](#)]
21. Adhikari, S.; Sinha, N.; Dorendrajit, T. Fuzzy Logic Based On-Line Fault Detection and Classification in Transmission Line. *SpringerPlus* **2016**, *5*, 1002. [[CrossRef](#)] [[PubMed](#)]
22. Pothisarn, C.; Klomjit, J.; Ngaopitakkul, A.; Jettanasen, C.; Asfani, D.A.; Negara, I.M.Y. Comparison of Various Mother Wavelets for Fault Classification in Electrical Systems. *Appl. Sci.* **2020**, *10*, 1203. [[CrossRef](#)]
23. Parikh, U.B.; Das, B.; Maheshwari, R. Fault Classification Technique for Series Compensated Transmission Line Using Support Vector Machine. *Int. J. Electr. Power Energy Syst.* **2010**, *32*, 629–636. [[CrossRef](#)]
24. Gayathri, K.; Kumarappan, N. Comparative Study of Fault Identification and Classification on EHV Lines Using Discrete Wavelet Transform and Fourier Transform Based ANN. *Int. J. Electr. Comput. Eng.* **2008**, *2*, 10.

25. Khoker, M.Z.; Prakash Mahela, O.; Ahmad, G. A Current Based Hybrid Algorithm Using Discrete Wavelet Transform and Hilbert Transform for Detection and Classification of Power System Faults in the Presence of Solar Energy. In Proceedings of the 2020 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), Bhopal, India, 22–23 February 2020; pp. 1–6.
26. Jayabharata Reddy, M.; Mohanta, D.K. A Wavelet-Fuzzy Combined Approach for Classification and Location of Transmission Line Faults. *Int. J. Electr. Power Energy Syst.* **2007**, *29*, 669–678. [[CrossRef](#)]
27. Youssef, O.A.S. Combined Fuzzy-Logic Wavelet-Based Fault Classification Technique for Power System Relaying. *IEEE Trans. Power Deliv.* **2004**, *19*, 582–589. [[CrossRef](#)]
28. Jiang, J.-A.; Chuang, C.-L.; Wang, Y.-C.; Hung, C.-H.; Wang, J.-Y.; Lee, C.-H.; Hsiao, Y.-T. A Hybrid Framework for Fault Detection, Classification, and Location—Part I: Concept, Structure, and Methodology. *IEEE Trans. Power Deliv.* **2011**, *26*, 1988–1998. [[CrossRef](#)]
29. Jiang, J.-A.; Chuang, C.-L.; Wang, Y.-C.; Hung, C.-H.; Wang, J.-Y.; Lee, C.-H.; Hsiao, Y.-T. A Hybrid Framework for Fault Detection, Classification, and Location—Part II: Implementation and Test Results. *IEEE Trans. Power Deliv.* **2011**, *26*, 1999–2008. [[CrossRef](#)]
30. Jamil, M.; Sharma, S.K.; Singh, R. Fault Detection and Classification in Electrical Power Transmission System Using Artificial Neural Network. *SpringerPlus* **2015**, *4*, 334. [[CrossRef](#)] [[PubMed](#)]
31. Singh, N.K.; Badge, S.S. A Novel Fault Detection and Classification Technique for Double Circuit Transmission Line Using Artificial Neural Network. In Proceedings of the 2017 International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICT), Kannur, India, 6–7 July 2017.
32. Sharma, P.; Saini, D.; Saxena, A. Fault Detection and Classification in Transmission Line Using Wavelet Transform and ANN. *Bull. Electr. Eng. Inform.* **2016**, *5*, 284–295. [[CrossRef](#)]
33. Parvez, I.; Aghili, M.; Sarwat, A.I.; Rahman, S.; Alam, F. Online Power Quality Disturbance Detection by Support Vector Machine in Smart Meter. *J. Mod. Power Syst. Clean Energy* **2019**, *7*, 1328–1339. [[CrossRef](#)]
34. Hojabri, M.; Dersch, U.; Papaemmanouil, A.; Bosshart, P. A Comprehensive Survey on Phasor Measurement Unit Applications in Distribution Systems. *Energies* **2019**, *12*, 4552. [[CrossRef](#)]
35. Sundaravaradan, N.A.; Mohanta, D.K. Robust Fault Analysis in Transmission Lines Using Synchrophasor Measurements. *Prot. Control Mod. Power Syst.* **2018**, *3*, 14. [[CrossRef](#)]
36. Zhang, N.; Kezunovic, M. Transmission Line Boundary Protection Using Wavelet Transform and Neural Network. *IEEE Trans. Power Deliv.* **2007**, *22*, 859–869. [[CrossRef](#)]
37. Chen, K.; Hu, J.; He, J. Detection and Classification of Transmission Line Faults Based on Unsupervised Feature Learning and Convolutional Sparse Autoencoder. *IEEE Trans. Smart Grid* **2016**, *9*, 1748–1758. [[CrossRef](#)]
38. Bhowmik, P.S.; Purkait, P.; Bhattacharya, K. A Novel Wavelet Transform Aided Neural Network Based Transmission Line Fault Analysis Method. *Int. J. Electr. Power Energy Syst.* **2009**, *31*, 213–219. [[CrossRef](#)]
39. Patel, M.; Patel, R.N. Fault Detection and Classification on a Transmission Line Using Wavelet Multi Resolution Analysis and Neural Network. *Int. J. Comput. Appl.* **2012**, *47*, 27–33. [[CrossRef](#)]
40. Fan, C.; Li, K.K.; Chan, W.L.; Yu, W. Study of Protection Scheme for Transmission Line Based on Wavelet Transient Energy. *Int. J. Electr. Power Energy Syst.* **2006**, *28*, 459–470. [[CrossRef](#)]
41. Aguilera, C.; Orduna, E.; Ratta, G. Adaptive Noncommunication Protection Based on Traveling Waves and Impedance Relay. *IEEE Trans. Power Deliv.* **2006**, *21*, 1154–1162. [[CrossRef](#)]
42. De Souza Gomes, A.; Costa, M.A.; De Faria, T.G.A.; Caminhas, W.M. Detection and Classification of Faults in Power Transmission Lines Using Functional Analysis and Computational Intelligence. *IEEE Trans. Power Deliv.* **2013**, *28*, 1402–1413. [[CrossRef](#)]
43. Tag Eldin, E.S.M. Fault Location for a Series Compensated Transmission Line Based on Wavelet Transform and an Adaptive Neuro-Fuzzy Inference System. In Proceedings of the 2010 Electric Power Quality and Supply Reliability Conference, Kuressaare, Estonia, 11–13 June 2010; pp. 229–236.
44. Jain, A.; Thoke, A.S.; Patel, R.N. Fault Classification of Double Circuit Transmission Line Using Artificial Neural Network. *Int. J. Electr. Syst. Sci. Eng.* **2008**, *2*, 750–755.
45. Tao, X.; Zhang, D.; Wang, Z.; Liu, X.; Zhang, H.; Xu, D. Detection of Power Line Insulator Defects Using Aerial Images Analyzed with Convolutional Neural Networks. *IEEE Trans. Syst. Man Cybern. Syst.* **2020**, *50*, 1486–1498. [[CrossRef](#)]
46. Junfeng, L.; Min, L.; Qinruo, W. A Novel Insulator Detection Method for Aerial Images. In Proceedings of the 9th International Conference on Computer and Automation Engineering—ICCAE'17, Sydney, NSW, Australia, 18–21 February 2019; ACM Press: Sydney, NSW, Australia, 2017; pp. 141–144.
47. Liu, C.; Wu, Y.; Liu, J.; Sun, Z.; Xu, H. Insulator Faults Detection in Aerial Images from High-Voltage Transmission Lines Based on Deep Learning Model. *Appl. Sci.* **2021**, *11*, 4647. [[CrossRef](#)]
48. Zhao, Z.; Zhen, Z.; Zhang, L.; Qi, Y.; Kong, Y.; Zhang, K. Insulator Detection Method in Inspection Image Based on Improved Faster R-CNN. *Energies* **2019**, *12*, 1204. [[CrossRef](#)]
49. Janicek, F.; Mucha, M.; Ostrožlik, M. A New Protection Relay Based on Fault Transient Analysis Using Wavelet Transform. *J. Electr. Eng.* **2007**, *58*, 8.

50. Masood, B.; Saleem, U.; Anjum, M.N.; Arshad, U. Faults Detection and Diagnosis of Transmission Lines Using Wavelet Transformed Based Technique. In Proceedings of the 2017 IEEE Jordan Conference on Applied Electrical Engineering and Computing Technologies (AEECT), Aqaba, Jordan, 11–13 October 2017; pp. 1–6.
51. Cabrelli, C.A.; Molter, U.M. Wavelet Transform of the Dilation Equation. *J. Aust. Math. Soc. Ser. B Appl. Math.* **1996**, *37*, 474–489. [[CrossRef](#)]

**Disclaimer/Publisher’s Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.