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Signal Processing Application Based on a Hybrid Wavelet Transform to Fault Detection and Identification in Power System

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Abstract: The power system is one of the most susceptible systems to failures, which are most frequently caused by transmission line faults. Transmission line failures account for 85% of all power system malfunctions. However, over the last decade, numerous fault detection methods have been developed to ensure the reliability and stability of power systems. A hybrid detection method based on the idea of redundancy property is presented in this paper. Because the continuous wavelet transform itself does not extract fault features for small defects effectively, the stationary wavelet transform approach is employed to assist in their detection. As a result of its ability to decompose the signal into high- and low-frequency components, undecimated reconstruction by using the algebraic summation operation (ASO) is used. This approach creates redundancy, which is useful for the feature extraction of small defects and makes faulty parts more evident. The numerical value of the redundancy ratio's contribution to the original signal is approximately equal to 36%. Following this method for redundant signal reconstruction, a continuous wavelet transform is used to extract the fault characteristic significantly easier in the time-scale (frequency) domain. Finally, the suggested technique has been demonstrated to be an efficient fault detection and identification tool for use in power systems. In fact, using this advanced signal processing technique will help with early fault detection, which is mainly about predictive maintenance. This application provides more reliable operation conditions.

Keywords: fault detection; stationary wavelet transform (SWT); continuous wavelet transform (CWT); Djibouti power grid; redundancy

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1. Introduction

Power systems, which are made up of three subsystems, are the most complicated systems ever created, making them one of the most fluctuating systems due to the undesirable variation of voltages and currents [1]. Despite the fact that the primary goal of power system engineers is to maintain the reliability and stability of the power system, it is nearly impossible to prevent the effects of breakdowns [2]. There are many factors that can cause power system outages, including unforeseen environmental conditions and human error [3]. They do, however, occur regularly in electricity transmission and distribution [1,4]. Moreover, transmission lines are responsible for more than 85% of power system faults [1,5]. Transmission lines (TLs) are prone to two types of defects: open circuit faults and short circuit faults. A short circuit fault, also known as a shunt fault, is an overvoltage situation that occurs suddenly, whereas an open circuit or series fault is a stoppage in current flow. Additionally, short-circuit faults in transmission lines are classified as symmetrical or asymmetrical. As the name implies, a symmetrical fault is a balanced fault in which all three phases are simultaneously short-circuited, while an asymmetrical fault shows the inverse [6].

Indeed, faults cannot be prevented; however, failure can be avoided if the defect is rectified as soon as possible [7]. Fault and failure are both contingency events; a fault is an unanticipated divergence from the standard condition in at least one of the system's major characteristics. A failure, on the other hand, is a permanent stoppage in a system's ability to accomplish a desired job under certain operating parameters [8]. Even faults might develop gradually from an unnoticeable slight deviation, resulting in significant maintenance costs [1]. In other words, there is a small defect that is unseen from the signal and causes disturbances in power systems. This small defect is recognized by transient phenomena, which may be classified into two categories. The first is when disruptions do not interfere with the regular operation of the system and can be classified as oscillation transients or impulsive transients. Those transients affect the quality of power, which may also perturb the equipment's performance for power distribution [9]. The others are the fault transients observed most generally in transmission line faults, which produce high-frequency components with abundant information [10]. The second sort of transient is a gradual degradation of equipment performance that should be monitored and discovered before it occurs.

To minimize maintenance costs, avert disasters, and achieve the purpose of power system engineers, the early detection of the fault is an important process in engineering [11,12]. Early detection, which is mainly based on a predictive maintenance approach, is the primary answer to the recurring problem in transmission lines. The sooner the problem is addressed, the better it is for the system. Predictive maintenance requests that the system be monitored for tiny deviations and then diagnosed by analyzing the signal to maintain the safety and reliability of the power supply [2,12]. One of the most important methodologies used for fault detection and diagnosis is signal analysis, which aims to discover a simple and effective transformation of the original signals [13].

Generally, the technique of condition monitoring is selected depending on the requirements of physical systems. Following that, fault detection and diagnosis are developed utilizing the monitored system's outputs [14]. Thus, signal processing techniques have been important in the field of fault diagnosis in industrial applications. As technology develops, new methodologies and approaches continually appear, providing more accurate, effective, and adaptive solutions for locating and minimizing faults across a variety of industries.

Indeed, wavelet and Fourier transforms are popular feature extraction methods because they can detect linked fault features with resiliency and precision [15]. Technically, the Fourier transform was not a good way to pull out features from non-stationary signals. However, the wavelet transform has been used a lot in fault detection and diagnosis applications because it can analyze a large amount of data.

Several studies have been conducted on early fault identification and diagnosis in power systems utilizing the wavelet transform [4,5,13,15,16]. Technically, the discrete wavelet transform (DWT) is more widely used than the continuous wavelet transform; thus, DWT decomposes the signal by using low- and high-frequency filters to obtain the detailed and approximate coefficients [17]. Furthermore, the selected detailed and approximate coefficients are helpful for fault detection as well as localization [8,18,19]. Following that, DWT is combined with another mathematical method to classify power system faults. There are several papers about the DWT and fuzzy logic techniques, the wavelet transforms (WT) and artificial neural networks, and the WT and neuro-fuzzy techniques [5]. These methods are effective in terms of finding every type of fault, but for small defect occurrences, it is recommended to use the stationary wavelet transform, which is a redundant transform [14]. Because of the benefit of redundancy, which produces a time-invariant structure across transformations, it is becoming popular in a variety of engineering applications [14]. Especially for instantaneous changes and transient faults, this method will make the small defect more visible and feature extraction easier.

In addition, not only the techniques of signal processing are emerging for power system applications, but various novel approaches have been developed for machinery. Machinery is indeed a core component of various industrial applications, and signal processing is fundamental to ensuring the reliability, safety, and performance of these machines across a wide range of industries. Some of the new methods are the similarity-based status characterization method, which offers a proactive and data-driven way to monitor gear surface wear, and the vibration-based prognostic scheme for gear health management in the surface wear progression of the intelligent manufacturing system. The aforementioned methodologies are employed to assess the gearbox in order to mitigate the propagation of surface wear, which can lead to hazardous failures and unexpected economic losses [20,21]. The implementation of a redundancy-based predictive fault detection approach was documented in reference [14]. This strategy was applied to address bearing detection issues by analyzing the vibration signal.

In this paper, a novel approach for fault detection is suggested. The proposed approach uses collected data from the Djibouti power grid Simulink model. Various fault types are simulated, and then a stationary wavelet transformation will be applied to decompose in a more understandable and visible way to detect the fault. The process is enhanced by choosing a mother wavelet. Following that, an algebraic summation operation will be used to reconstruct the signal. Observing the redundancy approach, the faulty area will be extracted easier with the help of the continuous wavelet transform.

Contribution

Historically, wavelet transforms, including continuous wavelet transform (CWT) and multi-resolution wavelet analysis (MRWA), have been employed for fault detection applications across several domains. In this study, the utilization of a redundant wavelet transform is employed due to the limited effectiveness of the MRWA in accurately identifying the features associated with transitory faults. These faults provide unique challenges in the characteristic extractions.

The primary contributions of this study are the employment of the redundancy property (RP) of the stationary wavelet transform (SWT) and the achievement of minimum phase shifting. The detection of defects can be effectively achieved by the utilization of the redundancy property (RP) of the stationary wavelet transform. However, it is worth noting that no existing approach in the literature has made use of this particular property (RP). Consequently, the fault signatures were enhanced through the use of a signal reconstruction model, resulting in improved ease and effectiveness of interpretation. The algebraic summation was used in a signal reconstruction model to illustrate the amplification of signals in the signal decomposition approach using a stationary wavelet transform. The redundancy ratio (RR) is calculated for each fault type, and it is approximately equal to 36%.

Furthermore, it has been found that the Haar wavelet offers advantages in terms of mitigating signal shifting in reconstructed signals. This study demonstrates originality and presents a novel perspective on issues related to defect detection.

Subsequently, the continuous wavelet transform is used to display the time-scale features of the reconstructed signals following the SWT application. As a result, the fault features are depicted on the time-scale plane.

The rest of the paper is organized as follows: A considerable amount of detail about the mathematical method is presented in Section 2. Section 3 describes the proposed methodology. Section 4 then discusses the simulation results. Section 5 covers the conclusions, limitations, and suggestions for further research.

2. Mathematic Background

The wavelet transforms (WTs), which were developed to overcome the constraints of the Fourier transform, are mathematical techniques for studying data such as signals or pictures with properties that fluctuate across multiple scales [13]. WTs have the advantage of excellent feature extraction, which puts them among the best methods of analysis. It works by breaking signals into shifted and scaled wavelets. Wavelet families can be observed as orthonormal, orthogonal, or biorthogonal [22,23]. The orthogonal and biorthogonal wavelet families have a linear phase feature that is beneficial in data reconstruction [24,25]. One of the fundamental advantages of wavelets is that they enable localization in both time and frequency domains at once. The second key advantage of wavelets is that they are extremely fast to compute when using the wavelet transform. In addition, the capacity of wavelets, which is to separate minor characteristics in a signal, is a key advantage. Wavelet transforms are decimated and undecimated operations depending on the type of WT, and WTs can extract local spectral and temporal information simultaneously [26]. Based on operation types, a WT can be considered redundant, which is a property that is not well approved due to its functions, but from another point of view, it is a popular and good method for small defects [14]. Small defects, considered invisible faults, can cause considerable damage. One of the popular methods is the stationary wavelet transform, which will be described in the following.

2.1. Stationary Wavelet Transform

It is deemed redundant due to the nature of the SWT computation. Yet, redundancy is useful in many engineering applications since it creates a time-invariant structure over transformations [27]. Redundancy, like anything else, has both advantages and disadvantages. One problem is that the approach is naturally slow, but its advantage is that it is simpler to define instantaneous changes and transients. As a result, the redundancy property is a useful tool for transitory signals since they are little faults that cannot be seen [8]. Additionally, it also helps to magnify the errors to characterize the properties of the defective signals.

In fact, SWT is recommended over DWT because of its capacity to recover the time-invariant structure, whereas DWT has lost this ability [14]. The DWT may be conceived of as the convolution process followed by decimation. This decimation procedure is skipped in SWT, and filter coefficients are up-sampled at each transformation level. In other words, SWT is a translation-invariance modification of the discrete wavelet transform, and it produces redundancy, which is an unseen property in MRA [27]. As a result, SWT is also known as the undecimated wavelet transform, which can sometimes be referred to as "Algorithm à Trous" in French. The process of decomposition of SWT is shown below, and according to Figure 1 [14], the signal is decomposed into low frequency, called the approximation coefficient, and high frequency, called the detail coefficient [14].

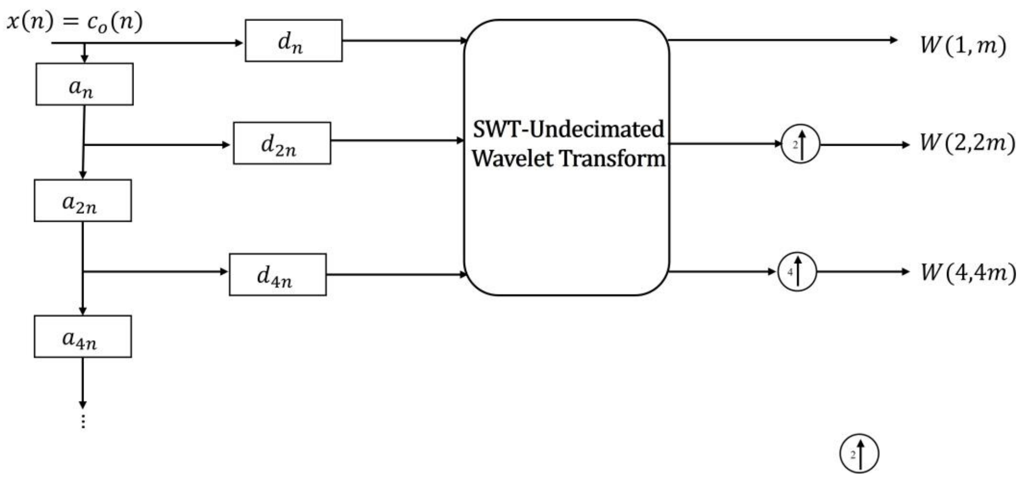

Figure 1. Stationary wavelet transform block diagram.

For reliable operation of a WT, it is crucial as well as challenging to choose the mother wavelet for characterizing the transient signal. The different types of mother wavelets found in the literature are Haar, Couflet, Daubechies, Symmlet, etc. [3,5,26,28]. The most commonly used ones are Haar and Daubechies; however, when it comes to power system fault signals, the Daubechies wavelet is the most suitable one [5,28,29]. Following that, the Daubechies mother wavelet makes the calculation short and fast for transient analysis [30]. For that reason, the Daubechies mother wavelet will be used in this paper.

2.2. Algebraic Summation Approach for Undecimated Reconstruction

Algebraic summation operation (ASO) is an operation for signal reconstruction [14]. Based on the purpose of this paper, an undecimated reconstruction operation is employed to benefit from the redundancy of SWT for fault detection. For this reason, ASO is performed, and its process is as follows. A block diagram showing ASO operation is shown in Figure 2.

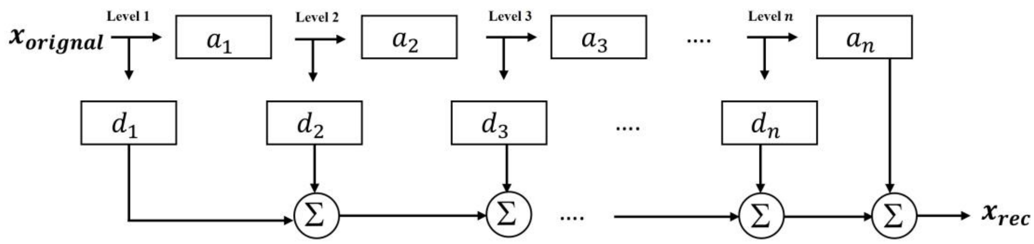

Figure 2. Block diagram for reconstruction using ASO.

As a result, finding the reconstruction signal entails adding up all of the detail coefficients and the most recent approximation [19].

$$x_{rec} = d_1 + d_2 + d_3 + \ldots + d_n + a_n \tag{1}$$

where d is the detail and a is the approximation. The reconstruction signal is amplified due to the up-sampling operation of SWT, and with it, the small defect is easily extracted.

2.3. Continuous Wavelet Transform

The continuous wavelet transform (CWT), similar to the other types of wavelet transforms, is a mathematical technique that is used to analyze and decompose signals or data into frequency components in both the time and frequency domains. It is especially effective for collecting non-stationary or time-varying signals. The CWT can be defined by the following formula for a signal $f(t)$ [28,31]:

$$CWT_f(a,b) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{a}} \psi^* \left(\frac{t-b}{a} \right) dt \tag{2}$$

where

$f(t)$ is the input signal being analyzed.
ψ^* is the complex conjugate of the mother wavelet.
a is the scale parameter, and it controls the width (frequency) of the wavelet.
b is the translation (time-shift) parameter.

Following that, the wavelet function—namely, the mother wavelet—must satisfy the admissibility condition defined as follows [31]:

$$\int_{-\infty}^{\infty} \frac{|\psi(\omega)|^2}{\omega} d\omega < \infty \tag{3}$$

$\psi(\omega)$ is the Fourier transform of the mother wavelet $\psi(t)$.
ω is the angular frequency.

In other words, the admissibility condition ensures that the wavelet function can accurately represent and reconstruct signals while preserving their essential properties [28].

Using CWT requires choosing specific families of mother wavelets, which include the following.

Generalized Morse wavelet ("morse") is a flexible and adaptable wavelet family that includes a wide range of oscillatory behaviors. This wavelet is useful for analyzing non-stationary and complex signals, since it can capture both narrowband and broadband properties [28,32,33].

Analytic Morlet wavelet ("amor") is a Morlet wavelet family member that is intended to capture and analyze localized oscillations and transient phenomena in signals. In fact, the Amor wavelet shape resembles a Gaussian curve modified by a sinusoidal oscillation. Because of this, the wavelet is appropriate for analyzing signals with both frequency and time fluctuations, especially in disciplines such as neuroscience for analyzing brain oscillations [34].

Bump wavelet ("bump") is a basic yet effective wavelet that is localized in both the time and frequency domains. This wavelet is ideal for identifying signal transitions and rapid changes [35].

In summary, these wavelet families have the purpose of representing various features of the signal. The wavelet family to choose is determined by the parameters of the signal being analyzed and the desired feature extraction. Because each family has distinct features, they are appropriate for a variety of applications.

3. Proposed Methodology

The proposed hybrid fault detection method in this study's major purpose is to determine the characteristics of abnormal voltage signals induced by short-circuit faults and transient phenomena. These signals are recorded from the Djibouti power grid model and an artificial signal, which is a combination of harmonic components as well as a healthy signal. The second step is the feature extraction of the recorded signals by hybrid wavelet transformation with the Daubechies wavelet as a mother wavelet. Daubechies wavelets, often known as "db" wavelets, are a family of wavelets with distinct vanishing points. They are capable of providing accurate time–frequency localization.

The hybrid wavelet transform is a combination of SWT and CWT. The procedure for the approach is as follows: Firstly, the collected signal is decomposed by the details and approximation coefficients by SWT, and following that, the algebraic summation operation (ASO) is applied to reconstruct the signal. The undecimated reconstruction amplifies the small defects, which is one of the easiest ways to make instantaneous changes. Then, the CWT is applied to the reconstruction signal because the redundant transformer makes the small defect more visible. Before applying the CWT, signal shifting for different Daubechies wavelet numbers is calculated to find the optimum one. The summary steps of the workflow for the suggested fault detection system are presented in Figure 3.

In this paper, Shannon's information criterion (SIC) known as the minimum description length (MDL) is used to determine the decomposition level using the following formula [36]:

$$L = log_2\left(\frac{f_s}{2 \times f_{min}}\right) \tag{4}$$

In fact, SIC is frequently used to guide the selection of the number of decomposition levels in wavelet-based signal analysis. The main idea is to choose the optimal level that provides a good representation of the signal feature and avoids overfitting [37].

In cases where the specified decomposition level number L is unsatisfactory, it is recommended to use a level between 1 and the detected 's SIC' number, as indicated in the following:

$$1 \leq L < SHI \tag{5}$$

$$L_{\text{optimum}} = \frac{SHI - 1}{2} \tag{6}$$

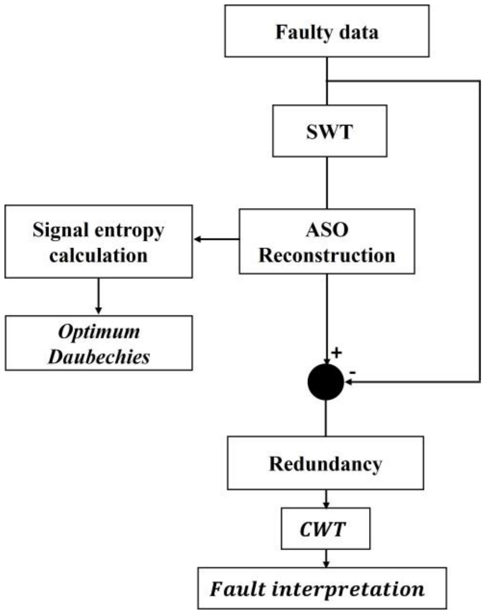

Figure 3. Summary of workflow steps.

The optimum level is the best level of decomposition to provide effective feature extraction while preserving signal information. As the result of this proposed methodology, to indicate the enhancement of the approach, a redundancy ratio (RR) is defined as below:

$$RR \triangleq \frac{\left|max\left(x_{original}\right)\right|}{\left|max\left(x_{reconctructed}\right)\right|} \tag{7}$$

3.1. Application on Djibouti Power Grid Model

The Republic of Djibouti is a small country in the Horn of Africa with a population of one million people. Furthermore, Djibouti is a country near the equator with only two seasons (winter and summer). Typically, the grid is described as two main 230 kV lines imported from Ethiopia with two types of voltage transformation [38]. The first one is a step-down transformer of 230/63 kV with 63 MVA; following that, there is another step-down transformer of 63/20 kV and 12 MVA. In this paper, one line, which is the Ali-Sabieh line (Figure 4) will be analyzed, and all calculations will be performed on it. The line is an overhead line with a length of 78 km, and it encompasses many components, including circuit breakers, transmission line, transformer, and load. Each block is composed of a primary side (ABC) and a secondary side (abc).

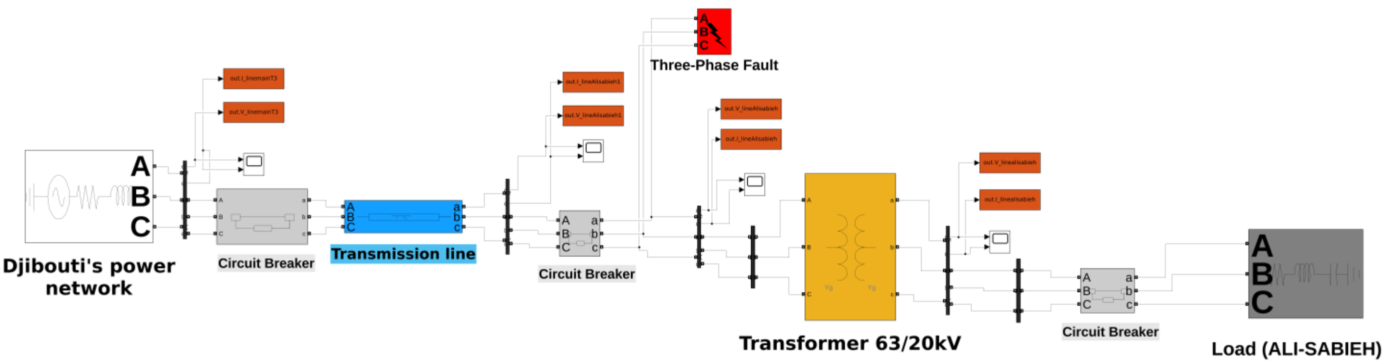

Figure 4. Proposed Simulink model.

In general, faults in transmission lines can be classified as open circuit or short circuit, as shown in Figure 5 [26]. Following that, the short circuits are more common than open circuits, and the latter are composed of two types, such as symmetrical faults and unsymmetrical faults. Thereafter, each type has sub-categories, which are mentioned below [26].

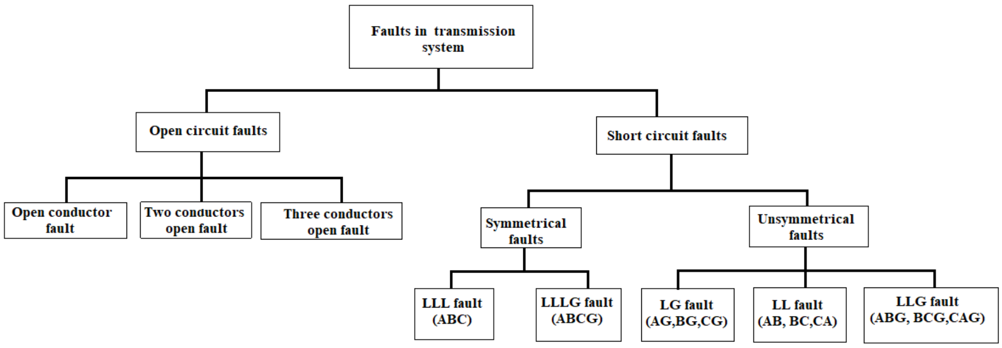

Figure 5. Fault classification at transmission lines.

3.2. *Artificial Signal*

The artificial signal is created to confirm the power of the SWT because this signal characteristic is known prior. Thus, the signal is a combination of 3rd and 5th harmonics with noise as well as a healthy signal. Indeed, harmonics are not something new; they used to be in power systems, and researchers have investigated solutions for avoiding the effects of harmonics in the system [9,39,40].

The causes of harmonics may not be found exactly, but they are mostly coming from power electronic equipment, arcing equipment as well as saturable devices such as aging transformers [41,42]. Moreover, the harmonic may also be created by short-circuit faults. For precise harmonic components such as the 3rd and 5th ones, these components demonstrate the non-linear load availability, and the noise shows the weak communication of the equipment as well as to make a simulation more realistic because in many real-world scenarios, signals are rarely perfectly clean and free of noise. The formula for the artificial signal is shown below:

$$x' = x_h + 0.5sin(2\pi f_3 t) + 0.6sin(2\pi f_5 t) + error \tag{8}$$

$$x_h = sin(2\pi f_o t) \tag{9}$$

$$error = 0.2n(t) \tag{10}$$

where x_h is the healthy signal, $n(t) \in N(0,1)$ and $N(0,1)$ represent the standard normal distribution, while f_o is the fundamental frequency at 50 Hz, f_3 is the third harmonic, and f_5 is the fifth harmonic.

The noise power of the error signal is proportional with the variance random signal and if so, for the added standard normal distribution in the simulation process, its power has unit value ($\sigma^2 = 1$). However, in this application, the noise power inserted in the artificial signal is approximately 4%, and it is found as shown below:

$$\sigma^2 = (0.2)^2 = 0.04 \tag{11}$$

Harmonics is challenging because it has a huge impact on power systems, and its effects start by heating the insulation, causing damage [43]. Thus, the 3rd and 5th harmonics are the more common components occurring in the system, and especially the 3rd harmonic has a rapid increase in current, which is very dangerous for the system [39,41,44]. For that reason, fault detection before any damage has occurred is essential to maintaining the stability of the power system.

4. Simulation Results on Predictive Fault Detection

The Djibouti power system model was used to simulate a short circuit in various scenarios. In the line between Jaban-as and Ali-Sabieh, three-phase faults (ALIS 63-1 and ALIS 20-1) were implemented. Table 1 below depicts the five fault categories, which include single-line-to-ground faults, double-line-to-ground faults, three-phase faults, three-phase-to-ground faults, and line-to-line faults.

Table 1. Fault type classification in power system.

Fault Type	Phase A	Phase B	Phase C	Phase G
A-G	1	0	0	1
A-B	1	1	0	0
AB-G	1	1	0	1
ABC	1	1	1	0
ABC-G	1	1	1	1

The simulation results are presented below after incorporating the short-circuit fault block into the model using MATLAB/SIMULINK R2023b. In order to achieve optimal continuity in the simulation and accurately capture the rapid transient events that occur in the power system, a sampling frequency of 20 kHz was initially chosen. However, it is advisable to pick a lower sample frequency than the one now chosen.

Figure 6 shows the signal representation of the different fault types such as single line to ground, line to line to ground, three phases, three phases to ground, double line to ground and the last one is the artificial signal that was created. According to the figure, a short-circuit fault emits a transient signal when it begins and when it is cleared. When a three-phase fault occurs, the voltage drops to zero, causing signal distortion and a significant rise in current. Only the voltage parameter is examined in this paper, since tiny defects caused by transient phenomena are noticed in this parameter. Following that, the chosen signal is based on the distortion size; hence, for A-B and AB-G faults, other phases were chosen rather than the faulty phases since the distortion size for the faulty phases was unimportant. As depicted in Figure 6, the signals had a duration of T = 0.2 s and were sampled at a frequency of 20 kHz. Hence, the number of data points, denoted as N, is determined by the following calculation:

$$N = 20000 \times 0.2 = 4000 \tag{12}$$

Alternatively, in the context of digital applications, the selection can be made based on the formula 2^n, where n represents an integer. In this case, the value of n is 12, resulting in 2^{12} equaling 4096 points, which is the closest approximation to the desired 4000 points.

It is difficult to derive the fault characteristic using a straightforward mathematical procedure. As a result of its redundancy technique, SWT becomes the best one to easily extract small defects.

To begin, the Shannon information criteria should be calculated to determine the level of signal decomposition. However, with a sampling rate of 20 kHz, the level of decomposition is equal to 7, and according to the optimum level formula, in this instance, it is equal to 3. In addition, the Daubechies wavelet number should be chosen to avoid any curve shifting. Therefore, for each fault type, the mother wavelet number is selected by calculating the signal shifting amount.

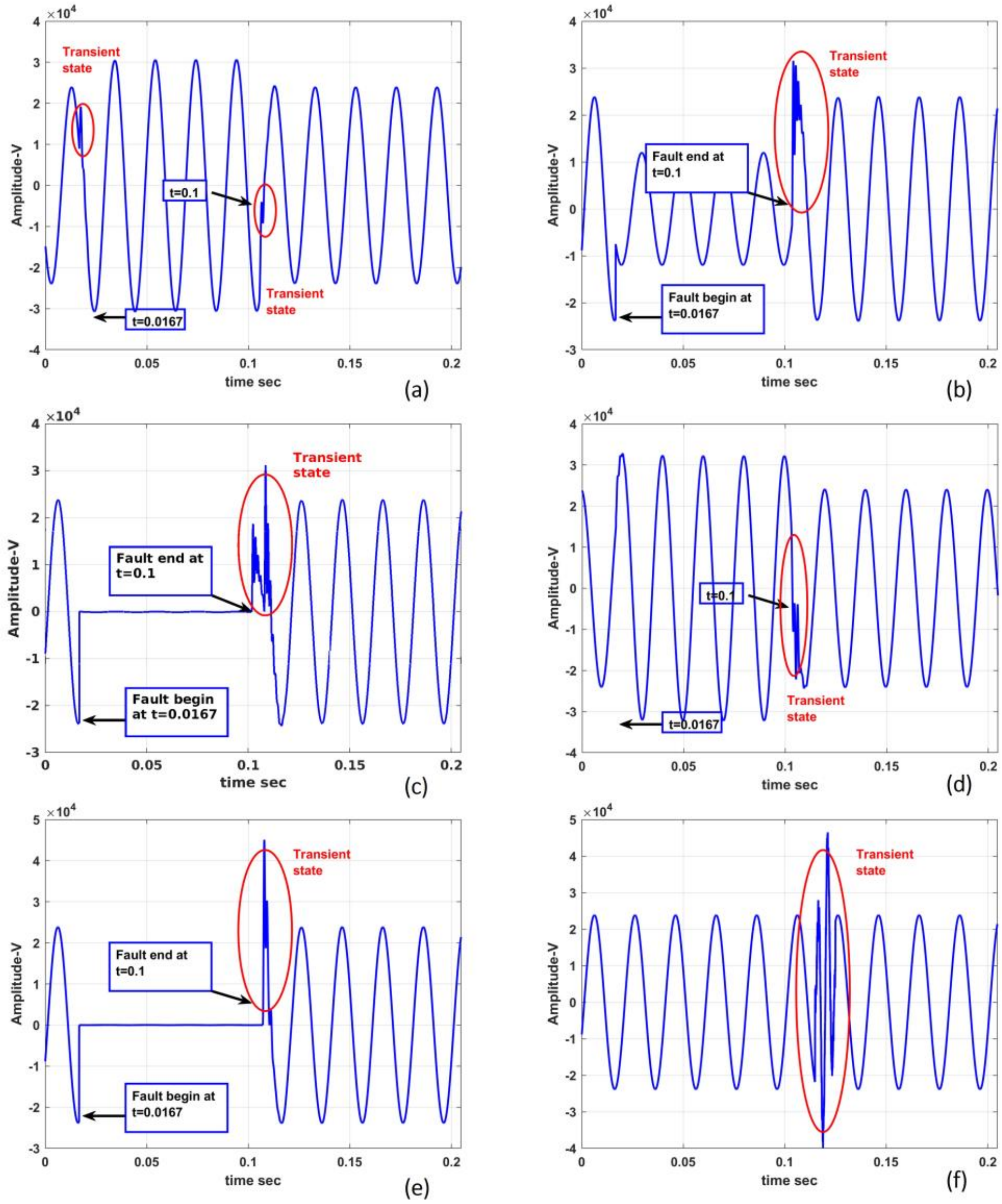

Figure 6. The signal representation for (**a**) A-G fault phase B, (**b**) A-B fault, (**c**) ABC fault, (**d**) ABC-G fault, (**e**) AB-G fault, and (**f**) Artificial signal fault.

According to Figure 7, the shifting shows the phase difference between the original and the reconstructed signals' waveforms. Hence, this figure indicates the shifting phase according to the Daubechies wavelet type (db#) to be used in this application. As a result, it is observed that the Daubechies number is proportional to the phase shifting distance. In other words, the higher the Daubechies number, the more visible signal shifting is found. For this reason, it is suggested that the least number of Daubechies is suitable to avoid any shifting.

The Daubechies wavelet with the filter coefficient [1, 1], also known as db1, shares the same approximation as the Haar wavelet. For that reason, db1 is known as the Haar wavelet, and it is suggested in this paper because the two signals, the reconstructed and the original signal, have zero shifting. The results of the decomposition for the chosen wavelet mother are shown in the following:

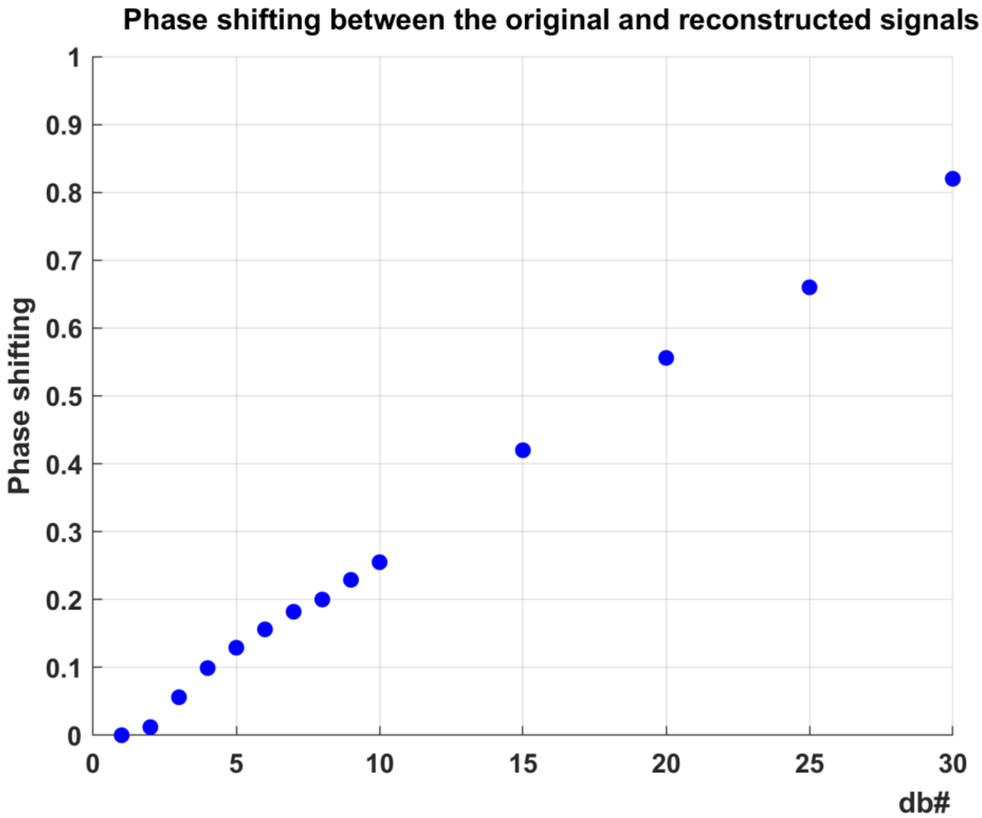

Figure 7. Shifting amount for the reconstructed signal and the original signal.

Figure 8 represents the signal decomposition using SWT for the approximation and detail coefficients of different faults. As the optimum level of decomposition is selected, three details and one approximation are observed, which are referred to as high frequency and low frequency as well.

Hence, it is observed from Figure 8 that for each sub-figure, a high frequency is shown at approximately 0.1 sec, which was the time disconnection of the short-circuit block simulation. The high frequency seen is from transient phenomena, which are defined as temporary events occurring in the system. In other words, it is a rapid change in the power system.

After this decomposition, its signal reconstruction is completed using the ASO operation. It is the summation of the three details and one approximation observed in Figure 8. The reconstructed signal has the same shape as the original signal, but it is only amplified. This technique is highly effective for easily extracting signals. In other words, the signal amplified is known as "redundancy", which is one of the popular properties of SWT. Redundancy is observed in Figure 9.

Due to the up-sampling approach of SWT, the redundancy is observed very precisely, and the small defects that were difficult to extract become rapidly and easily extracted. For the redundancy ratio as defined in Equation (7), RR is approximately determined as 0.36.

Using db1, which is similar to a Haar wavelet, the reconstruction signal and original signal have zero shifting. However, the order of Daubechies was determined by calculating the shifting amount of the signal, even though, in the literature, some researchers suggested that the Daubechies wavelet function types db8 and db4 are good for signal de-noising and fault detection problems [3,29,45].

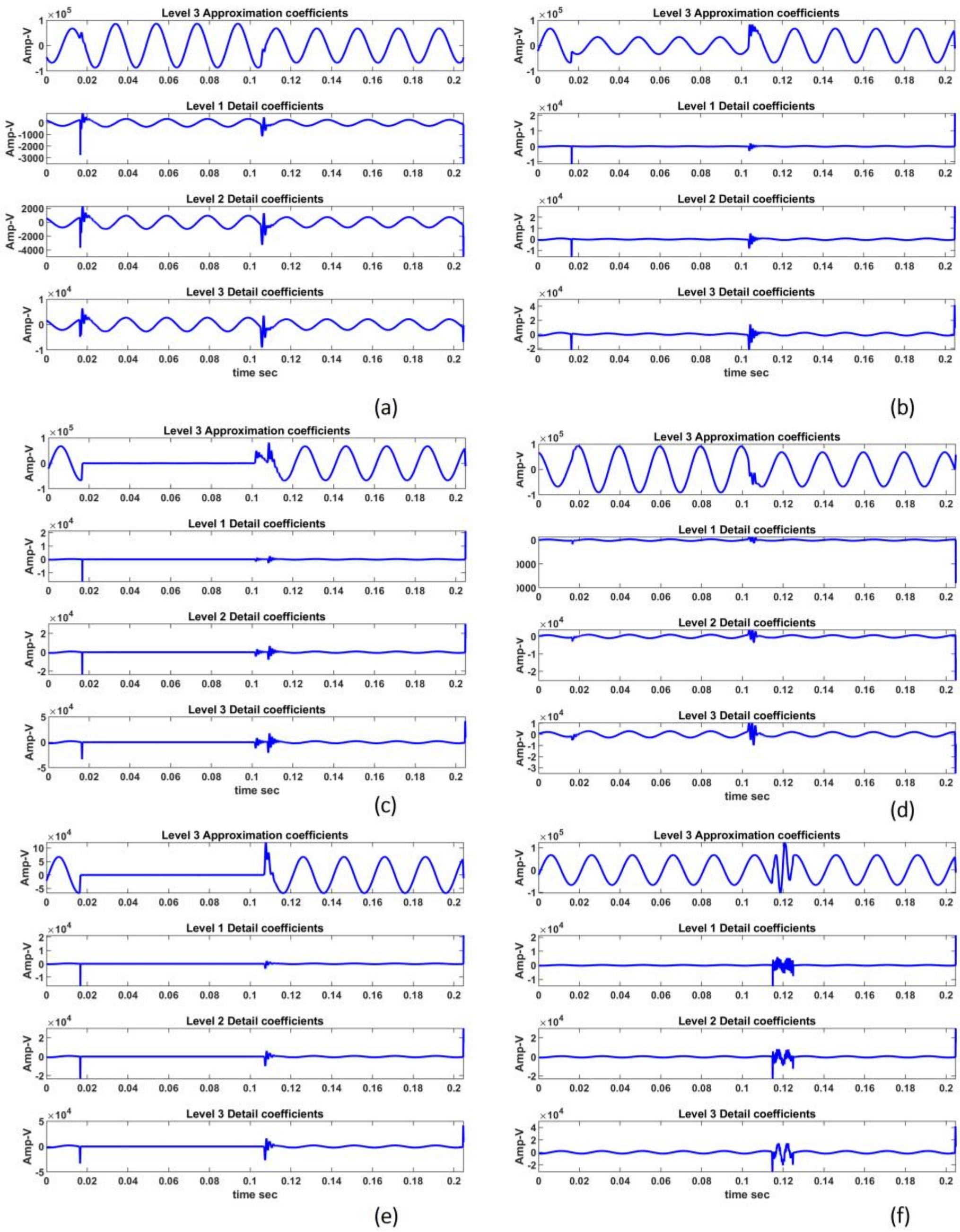

Figure 8. The signal decomposition using SWT for (**a**) A-G fault phase B, (**b**) A-B fault, (**c**) ABC fault, (**d**) ABC-G fault, (**e**) AB-G fault, and (**f**) Artificial signal fault.

The Haar wavelet has been calculated without a temporary array, and it is based on discontinuity, which makes it discontinuous and look like a step function as well. Once the reconstruction is completed using ASO with the advantage of redundancy, the wavelet transform is applied to extract features of the transient signal. Precisely, the continuous wavelet transform is used with different mother wavelet families depending on the suitability of the signal. For CWT, analytic wavelets are used to determine time–frequency parameters [14].

Consequently, for each fault type, a unique mother wavelet is used, which is described in the following Table 2 [40].

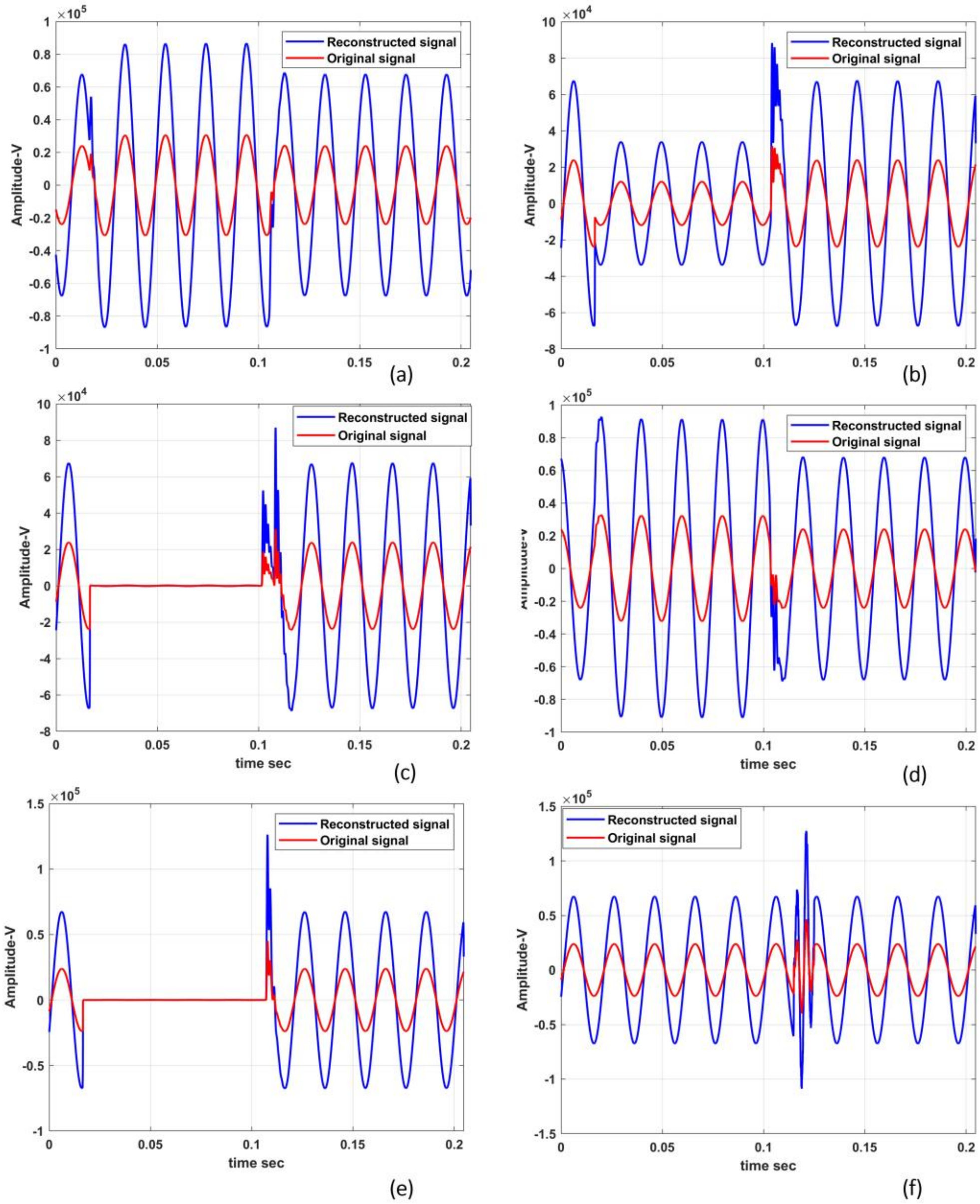

Figure 9. Double plot for reconstruction and original signals for (**a**) A-G fault phase B, (**b**) A-B fault, (**c**) ABC fault, (**d**) AB-G fault phase C, (**e**) ABC-G fault, and (**f**) Artificial signal fault.

Table 2. The mother wavelet family selected for the different fault types.

Fault Type	Mother Wavelet Selected
A-G	'bump'
A-B	'amor'
AB-G	'amor'
ABC	'morse'
ABC-G	'bump'
Artificial signal	'morse'

Depending on the type of fault as well as the distortion form, the mother wavelet family type has been selected. For instance, an A-G fault typically exhibits a relatively small defect that is not easily discernible in the time domain. Consequently, a bump wavelet is deemed appropriate for detecting and characterizing such faults. The amor wavelet is a mother wavelet commonly employed for fault types characterized by sinusoidal oscillation, such as AB and AB-G. The Morse wavelet, as the third mother wavelet, is well-suited for a wide range of oscillatory phenomena, including ABC and artificial signals. Once the mother wavelet has been chosen, the result from the continuous wavelet transform is shown in Figure 10.

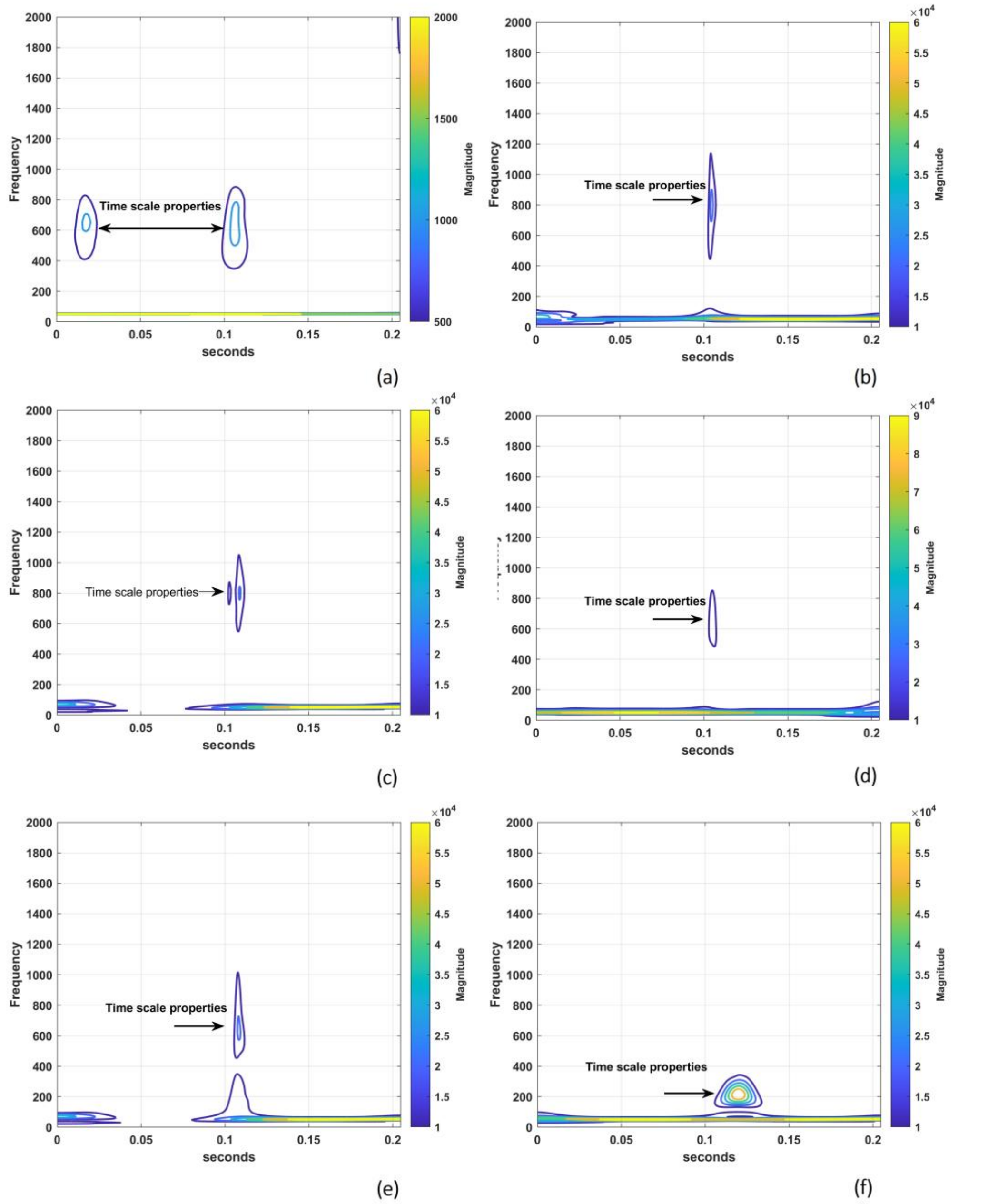

Figure 10. Wavelet transform application on signals: (**a**) A-G fault phase B, (**b**) A-B fault, (**c**) ABC fault, (**d**) AB-G fault phase C, (**e**) ABC-G fault, and (**f**) Artificial signal.

In fact, a small defect is hard to detect because of its characteristic; therefore, using the up-sampling approach, this hidden characteristic is easily extracted. Following the undecimated reconstruction approach using the ASO operation, the original signal has been amplified, which makes the extraction easier using the continuous wavelet transform. Figure 10 represents the spectrum in which the fault characteristics are observed. In Figure 10, there are six sub-figures, and the first five sub-figures show the spectrum for the recording signal from MATLAB Simulink R2023b, and the last one is about the artificial data.

Table 3 below illustrates the fault characteristics detected from the spectrum shown in Figure 10.

Table 3. The fault characteristics detected from the spectrum.

Fault Type	Fault Time Detected	Frequency Detected
A-G	0.01667–0.1167 s	600–650 Hz
A-B	0.1167 s	800 Hz
AB-G	0.1167 s	800 Hz
ABC	0.1167 s	700 Hz
ABC-G	0.1167 s	700 Hz

As mentioned above, the fault characteristics are shown in the table, and they have been recorded using the spectrum from CWT applied to recorded signals. From Table 3, the frequency components observed from the simulation are the 12th, 13th, 14th, and 16th. These frequency components were detected due to the faults that occurred in the power system. Thereafter, the undecimated reconstruction helps to clearly extract the small defects because the same methodology was applied to the artificial signal, which has an added known characteristic, and it shows that the method is effective. In fact, faults can always be seen physically, but small disturbances that have a real impact on the system cannot be observed. Consequently, the redundancy found by the undecimated reconstruction approach is powerful for power system faults, especially for small disturbances.

Figure 10f confirms the capability of characteristic extraction of the proposed methodology. Since the frequency components added were the 3rd and 5th harmonics, from the mathematical method used, the frequency detected is 250 Hz, which is the 5th harmonic. Because the entire artificial signal was not inserted, only the fifth harmonic is identified. From this result, it can be concluded that the proposed methodology is suitable for the small defects detected in the power system.

The accuracy of the developed technique is based on the stationary wavelet transform (SWT). The power of the contribution is hidden in the SWT as well. In decomposed signals by the stationary wavelet transform, the signal reconstruction is completed with the help of the minimum phase shifting (minimum phase distance), which is provided by db1, or Haar wavelet function. This minimum shifting amount is a measure of the accuracy of the data used in the study. Also, the stationary wavelet transform is a redundant transform, and then it shows the amplifications of the fault signatures in the minimum phase condition.

5. Conclusions

Faults in transmission lines are the most prevalent because they damage the protective systems and, more importantly, ruin the electrical equipment. For that reason, it is crucial to monitor the equipment by analyzing the signals to detect faults and extract features as well. However, there are small defects that are unseen on the signal, and their effects are observed drastically. This type of fault is the most dangerous since it is invisible. Consequently, the undecimated reconstruction approach using SWT is useful for these types of faults because it produces redundancy, which is an approach that amplifies the small defects to make it easier to extract the feature. In this paper, the proposed methodology is to decompose the signal by using SWT, and the decomposition level is chosen by Shannon's information criterion, in which the optimum level is selected by the mean of the minimum level and the calculated level. Following that, the undecimated reconstruction using the ASO operation approach is applied. Thus, the redundancy property helps the feature extraction, and using the continuous wavelet transform, the findings show that 12th, 13th, 14th, and 16th harmonic components are observed in the spectrum. Without the undecimated reconstruction, these features were unfound, and due to this approach, the features were extracted easily and rapidly due to the precise wavelet mother type of continuous wavelet transform. To verify the success of the method, the proposed methodology was applied to a known feature added to an artificial signal, and as a result, it was found that the proposed approach is efficient for the small disturbance found in the power system. In terms of the comparison with other methods, fault detection is used in the frequency domain directly, but here, the small defects (or transients) are amplified in the time domain; after that, these amplified signals are transformed to the time–frequency (or scale) domain. Hence, the performance of this study is provided by an easy detection approach with the help of the definition of redundancy ratio as given in Equation (7).

Overall, this proposed method can be generalized to any small defects that may occur in a power system. For future work, it is recommended to simulate other types of signals to confirm the effectiveness of the proposed detection approach. In terms of a more practical application, an intelligent robot moving along the lines can be used to collect data from some cracks in the insulators and the slack cable connection. Simultaneously, these data will be transferred to the computers to make the final decision using the proposed mathematical methods.

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