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Improved Technique to Diagnose Fault in IEEE Standard 14-Bus System

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Abstract: ***This study presents a new technique for fast detecting and diagnosing of power grids faults. Discrete Wavelet transform (DWT) has a major disadvantage of noise sensitivity. The proposed technique solves the problems of DWT, where a high-precision classification of noisy and faulty signals could be obtained. Fusion between voltage and power readings is done to provide a more reliable and accurate decision to determine the exact location of the fault. In this technique, the learner classifier is used,and the system is trained for multiple situations where most faults may occur. All simulations were carried out and performed on the standard IEEE 14 bus system to check the efficiency and performance of the technique proposed. Simulation results demonstrate, as will be discussed, a strong effectiveness of the suggested approach relative to others. The main feature of the proposed technique is that it can differentiate between faulty and noisy signals and recognize the fault's location quickly and with high reliability.***

Keywords Fault diagnosis, IEEE standard 14 bus system, Power quality, Data fusion, DWT, Smart grids.

I. INTRODUCTION

Research on fast detection and diagnosis of faults has been increasingly developed over the past several years. Fault analysis is intended to recognize the presence of faults in the system being observed, while fault diagnosis is intended to determine the triggers of the faults Electrical device components are used in power grids.[1]Detection of faults is used to locate faults in real time, as soon as possible and as reliably as possible. The important side to track the system in order to evaluate its safety and reliability. Detection of fault is critical for the safe operation of a system in many applications. To determine the location and time of the system. [1]

It is usually possible to identify error avoidance as the method of detection and diagnosis of faults. [2] If a fault is found, fixes will be made quickly and complete security features will be restored.

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For situations where improvements cannot be carried out readily, alternate security is put into service and activities are moved to a secure, safe state until the fixes can be completed. [2]

Nonetheless, both early detection and correct diagnosis of early defects lead to rapid unplanned maintenance and brief downtime for the system being regarded. [3]

We often prevent the negative and sometimes shocking effects of errors or faults. [3]Fault detection is the method of evaluating and matching calculated device details and system status data with an acceptable range of observable parameters to decide whether certain variables fell outside the scope reflecting the healthy state of the mechanism. [2]

Detection of fault identifies the event of failure in the process being tracked. This consists in identifying faults in systems, actuators and sensors through the use of dependencies between various observable signals. Even linked activities are fault identification and fault isolation. Fault identification determines the severity (size) of the fault, whereas fault isolation defines the position and form of fault. Fault isolation and fault identification are together referred as fault diagnosis, [4]. The aim of fault analysis is to determine the type of fault with as many information as possible, like the size of the fault, position and detection time [5].

Power systems are imperative to maintain the unwavering quality and legitimacy of power suppliers and to conduct a faulty signal check, identify and diagnose fault areas in a timely manner [6]. Also, if the case of energy systems failure, e.g. short circuit fault, it could spread and proliferate quickly in all areas of the appropriate systems, and the power grid may cause additional problems. For example, circuit breakers and various relays are routinely ineffective and clumsy inferable from the impact of fault dispersal and uncertainty in all parts of the power grid, ancient approaches for analyzing the fault were established [7].

In this manner, the constant voltage measurements and discrete data collected from the circuit breakers are very essential to construct the ability for fault determination and identification in the clever networks [8], [9].

Data from the Phasor measurement unit (PMU) is used to discover the place of fault for smart systems. Finding and discovering defective signals has advanced towards becoming widespread stock in power systems [10], [11], and [12]. Voltages and currents are dictated by using PMU that receives synchronization indications from global positioning system (GPS) satellites [13]. For these purposes, the PMU measurements are real extremes [10] and it is not nice to interface them anywhere in the power systems.

Thus, it is across the board to use the least amount of PMUs and compute voltage at all hubs of different devices using the most commonly known link as an Ohm principle [11].
Different information from different sources to the database structure makes a more stable and consistent affluent database than a single source [14], this is attributable to the fundamental techniques of data fusion strategies, and the results are appropriate and legitimate in the event of faulty information.
As of late, data fusion processes have been widely used in distinct regions wherever fundamental management processes can be enhanced where countless information are available from distinct sources [14].
This article's main innovation is how to show the new technique results are overcome to other distinct techniques. In power grids, the CB data cannot be reliably inferred from a rapid dispersal of the fault that travels more than one CB in the power grid in the case of a fault. In this manner, different CBs respond with fault as often as possible rely on the seriousness of the fault where the identification of cautious region of fault is extremely difficult. The suggested approach distinguishes and acknowledges the place of fault based on the energy measurement of each signal where the complex tree classifier specifies that the signal is faulty or not, in case of defective signal the new technique recognizes its accurate place.
The remainder parts of paper are planned as: part 2 presents the literature survey of the theories used. The new proposed method design and structure criteria are presented in part 3. IEEE standard 14 bus system is used to show the simulation studies to support the new suggested technique with respect to individual smart techniques in part 4 with their figures. Finally, the conclusion briefly is delivered in part 5.

II. SUGGESTED TECHNICAL BACKGROUND MECHANISMS

Previous research on identifying the place of faults relied on the DWT and data fusion methods [15], so this section will illustrate briefly how DWT can be used to determine the disturbance of any signal. The new technique depends on a decision Tree classifier; classification with its separate techniques will be described with more explanation for the decision Tree classifier.

A. Discrete Wavelet Transformation (DWT)

A wavelet is a "little wave" that has its vitality accumulated in time. It can create a number of analysis such as time-varying, non-stationary, and transient instances [16]. Malat explored the operator's characteristics that approach a signal at a specified resolution [16]. He showed that the difference of information between the approximation of a signal at the resolutions 2'+' and 2j can be extracted by decomposing this signal on a wavelet orthonormal basis of $L_2(Rn)$. This decomposition defines a multi-resolution orthogonal representation called the representation of a wavelet. It is calculated using a pyramid algorithm based on quadrature mirror filters convolutions [16].
Wavelets are fluctuations-like waves and oscillations contain centralized resources and characteristics in frequency and time domains [17], [18]. The orthogonal property and prior characteristics are more appropriate for tracking signals and fault diagnosis [19]. The signal may be presented using a collection between wavelet decomposition and scaling functions at variant locations (positions) and scales (durations) [19], [20]. Malat introduced the DWT framework, known as (MRA) for planning any signal to altered decision-making levels [20]. So, suppose y (x) ∈ $W_2(S)$ where orthogonal wavelets and their scaling functions are displayed as linear combinations [17]:

$$\mathbf{y}\,(\mathbf{x}) = \sum_{k=-\infty}^{+\infty} \mathbf{a}_{0,k}\boldsymbol{\varphi}_{0,k}(\mathbf{t}) + \sum_{n=-\infty}^{0}\sum_{k=-\infty}^{+\infty} \mathbf{d}_{n,k}\boldsymbol{\psi}_{n,k}(\mathbf{t}) \qquad (1)$$

$$\boldsymbol{\varphi}_{n,k(t)} = 2^{-\frac{n}{2}}\varphi(2^{-n}t-k); n,k\epsilon Z \qquad (2)$$

$$\boldsymbol{\psi}_{n,k(t)} = 2^{-\frac{n}{2}}\psi(2^{-n}t-k); n,k\epsilon Z \qquad (3)$$

Such as $\boldsymbol{\varphi}_{(t)}$ and $\boldsymbol{\psi}_{(t)}$ Specify the scaling function and orthogonal wavelets, respectively. Also n and k are the factors of dilation and translation. Wherever 2 $^{-n/2}$ term is attached to the wavelets and scaling functions to normalize them. Where $\mathbf{a}_{0,k}$ and dn,k are calculated as [14]:

$$a_{0,k} \;=< y, \boldsymbol{\varphi}_{0,k} > \qquad (4)$$

$$d_{n,k} \;=< y, \boldsymbol{\psi}_{n,k} > \qquad (5)$$

The decomposition of the signal based on the MRA method is shown in Fig. 1. And thus the two significant coefficients could be depicted as coefficient of detail (CD_1, CD_2, ..., CD_n) and coefficient of approximation (CA_1, CA_2, ..., CA_n) [20].

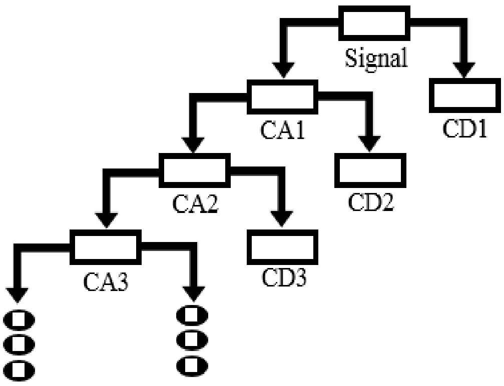

Fig. 1 MRA method with its details and approximation coefficients [15].

B. Classification

The selection of a classification algorithm is usually based on a number of variables, including software accessibility, ease of use, and efficiency, as measured by general classification precision [21]. The maximum likelihood (ML) method is the algorithm of choice for many customers due to its ready accessibility and the fact that it does not require an expanded training process [21]. Researchers are now widely using artificial neural networks (ANNs) as one of the most efficiency systems [21].
The use of decision trees (DTs) has increased over the past few years to classify remote sensed data. Method proponents claim to have a number of advantages over the algorithms ML and ANN. The DT is computationally quick, does not create statistical assumptions, and is capable of handling information represented on various measuring scales.

Software is readily available on the Internet to implement DTs. Pruning of DTs can make them smaller and more easily interpretable, while the use of boosting techniques can improve performance[21].

Classification is one category of supervised machine learning where an algorithm "comprehends "toclassify novel observations from samples of categorized data. To recognize classification models, use the MATLAB Classification Learner application. For more flexibility, we can permit feature or predictor data with its corresponding responses, to train the regression models, like, regression trees, logistic regression, support vector regression, and Gaussian process regression.

The MATLAB Classification Learner application exercises models for classification the data. Using this application, supervised machine learning is explored by using several classifiers, also we can explore our data, train models, select features, assess results schemes, and specify cross-validation, also we can execute automated training on the way to find the best type of classification model, inclusive decision trees, support vector machines, discriminant analysis, logistic regression, ensemble, and nearest neighbor's classification.

- **Complex tree classifier**

The complex tree technique is a strong statistical methodology that has several potential applications in scientific research for classification, estimation, analysis, and data manipulation. The following benefits are the use of decision tree models to explain research findings:Through splitting the original input variables into large subgroups, it simplifies complex relationships between input variables and target variables, Simple to read and understand, and Simple to handle lost ideals without resorting to imputation. So for previous explanation, complex tree classifier is used in proposed technique.[22]

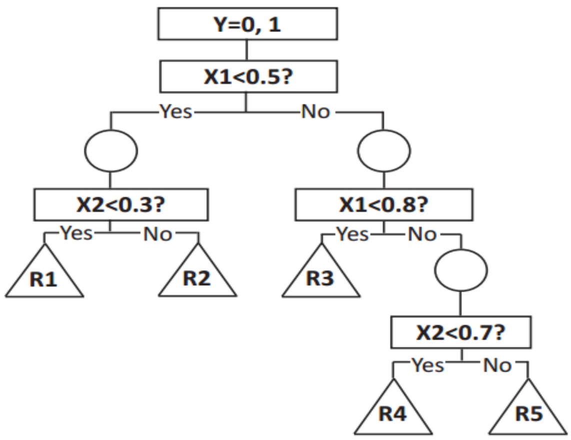

Fig. 2 a simple decision tree model[22]

Figure 2 displays a straightforward decision tree template consisting of a single conditional target parameter Y (0 and 1) and two continuous factors, x1 and x2, varying from 0 to 1.[22] A decision tree model's main components are nodes and branches and breaking, halting, and pruning are the most important steps in building a model.[22]

III. DESIGN CRITERIA AND METHODS FOR THE PROPOSED TECHNICAL STRUCTURES

The design criteria of the proposed technique will be demonstrated at this section by: explaining the suggested fault diagnostic unit based on discrete transformation of the wavelet, and also applying the structure of the proposed new technique to detect fault with each faulty or noisy signal.

A. Fault detection based on DWT

Daubechies and Haar are the most well-known wavelet scientists. DWT's vital orthogonal and locality aspects make it a highly unwavering approach to the quality of studying non-stationary signals [23], [24]. In Fig. 3, the faulty signal and waveform of the DWT are outlined. The sampling time is the horizontal axis and the cephalic axis is graded per unit. It is shown that the detail coefficient1 (CD_1) involves the high frequency signal and exposes the faulty signal to fast changes and can be used to define the fault time. It also shows that in locations where the value of CD_1 is essential, a fault or the effect of the fault may occur. Thus, the amplitudes of the CD_1 are compared with each other in likely defective places. The one with maximum amplitude would be the primary defective bus bar and it can be proclaimed as the fault place. But DWT has a significant issue as it does not discriminate between defective and noisy signals where, if there is any noise, DWT alarms the presence of fault. This will be discussed in the next parts with actual figures.

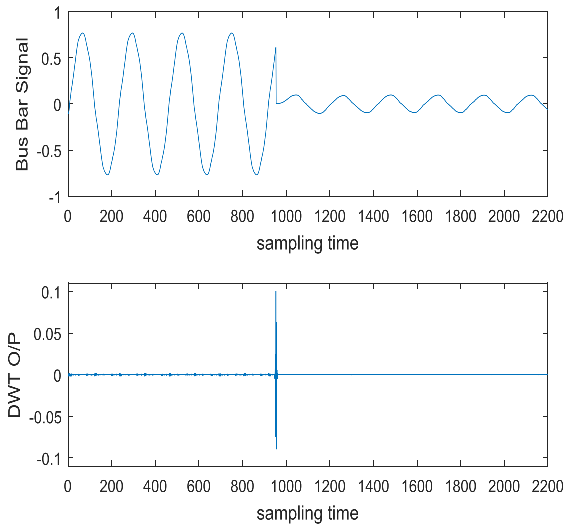

Fig. 3 The defective signal of the bus bar with its DWT.

B. The suggested strategy structure

The IEEE standard 14 bus system is used in this section to delineate a technique for recognizing the faulty region and its occurrence interval. For this purpose, the structure calculates the vitality of the obscure signal, At that point, the suggested model checks whether there is a faulty signal or not based on a decision Tree classifier that rehearses more signals and the model is prepared when any obscure signal can be classified as noisy or faultyemphasis on the estimation of signal energy as a summation of square sample values for all signals. For the same duration, this will impact the energy value of the signal in the case of a fault as the value for some specimens will be equivalent to none or zero in case of line to ground fault. Furthermore, if the situation is faulty, the strategy will try to determine where the fault occurs at any bus bar despite the fault location of the signal fluctuation where the largest difference values demonstrate the fault location of the faulty
bus bar,

Power calculations are determined for all incoming signals from all bus bars and comparison is created between variations between energy measurements where the more shifts in its value are the more faulty bus and so on. However, in the event that the status is a "noisy signal," no fault will be recognized depending on the choice of the classifier learner.

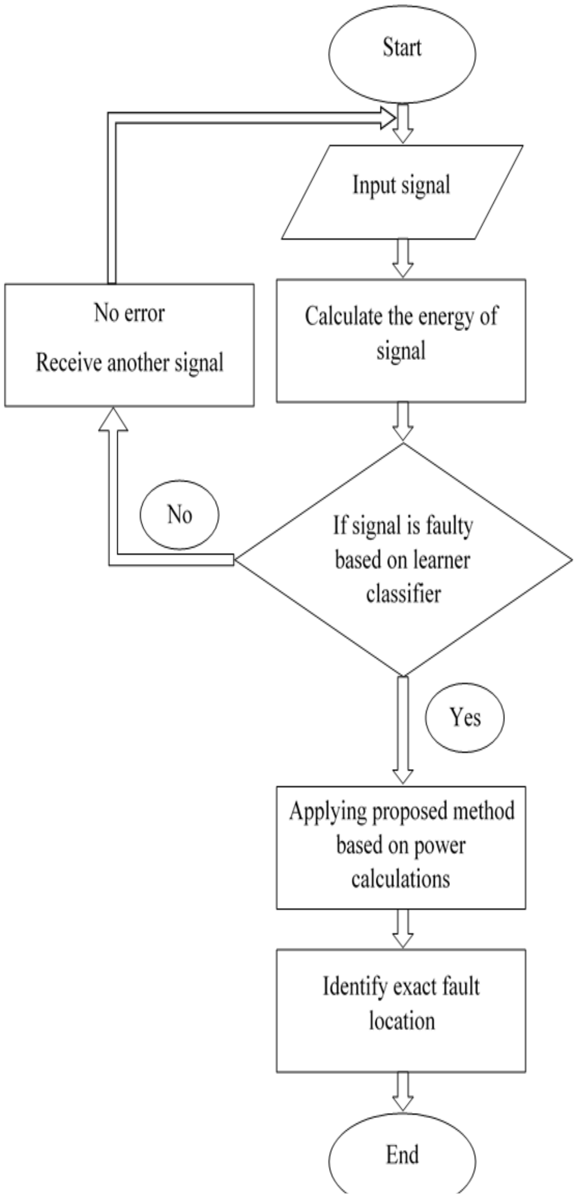

Fig. 4 The flow chart of proposed method.

IV. SIMULATION STUDIES AND RESULTS

IEEE standard 14 bus system case is used to illuminate the suggested strategy to the fault region, as stated by the suggested model when testing the FDD performance for any framework, circumstances are as follows:

A. IEEE Standard 14 bus system fault situations

The IEEE standard 14 bus system can be used as one of the real study systems because of its match in structure and ongoing unpredictability in comparison to micro grids [25]. Single line diagram system for standard IEEE 14 buses is shown in Fig. 4. Multiple faults are acquainted with the system to be asserted at changed positions in order to test the reliability and consistency of the suggested model.

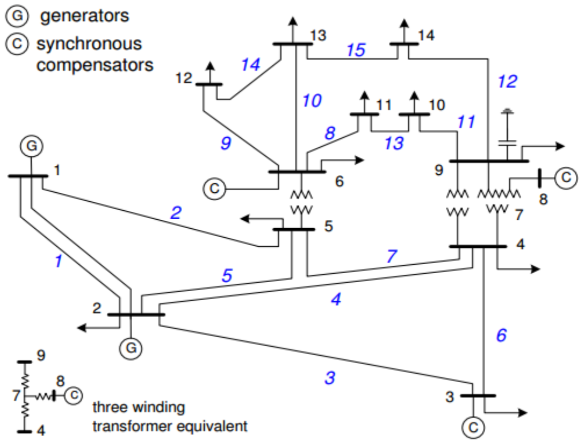

Fig. 5 Single line diagram for standard IEEE 14 bus system [26].

B. Results and discussion

In view of the methodology described in section 4. The work is divided into two parts for faulty and noisy signals.

- **Faulty Signal**

The examination signal on bus 4 and the correlation of DWT where the ground fault happens at the recorded index of 953 are shown in fig.6. Bus 3, the closest to bus 4, has a huge effect. In customary systems, faulty CBs faculties through any power system at an early stage, but they cannot recognize the particular fault region although near fault busses can be more affected than far-off buses. The two CBs of buses 4 and 3 have the activity of tripping due to the real fault of the 953 inspection index. Fig. 7 Demonstrates the defective signal of bus 3 and its DWT. DWT yield outlines varieties in signal where the CD_1 estimate in bus 4 changes from nearly nil to 0.1003 Pu at the 953 examining time index, as well as in bus 3 comparing ascents as the most extreme incentive to 0.0289 Pu. In these lines, DWT inquiry, through the example recorded index of 953, acknowledges the fault region at bus 4. In elective buses, the relative estimate of CD_1 is less than 0.1003 Pu in perspective of the vast separation from bus 3 and others. However, the DWT can pronounce the presence of defective signal, the abnormal state noisy system. Since CD_1 transmits the most severe recurrence signal like a loud signal. Consequently, FDD cannot use DWT alone but can be used with any combination approach or fresh method developed in this document. Fig. 8 demonstrates the output of the suggested approach for CBs, DWT and new FDD technique. We can see from Fig. 8 that DWT approach acknowledges a defective signal on bus 4 at the 953 index sample. Additionally, the recommended new strategy recognizes faulty signal at bus 4 at the sample index of 953. The new strategy is used to enhance the recognizable proof of fault. Where delay time is reduced, however, the newly developed approach is more reliable and faster than DWT, the unwavering quality in distinguishing evidence of the region of fault is extended. At other cases applied on DWT systems the sample at which disturbance occurred may be delay for one or more samples which is evidence of the high quality of new FDD technique as next figures. As there is no sample delay at proposed technique, method is less time consuming than the others such as DWT or radial basis function , as in [15].

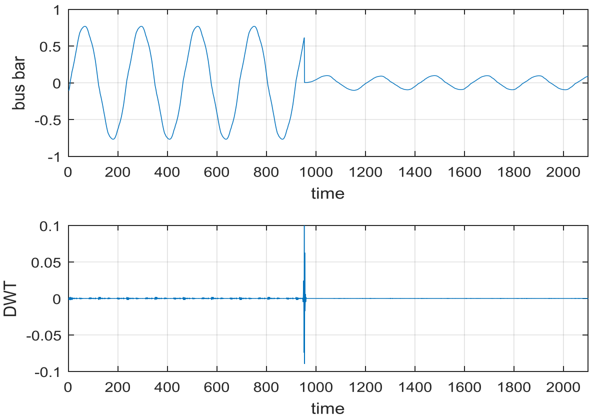

Fig. 6 Faulty bus with a sample index of 953 and its respective DWT.

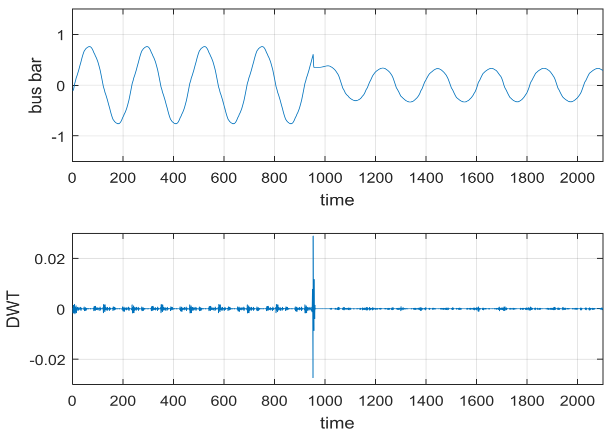

Fig. 7 Phase A of bus 3 and its respective DWT.

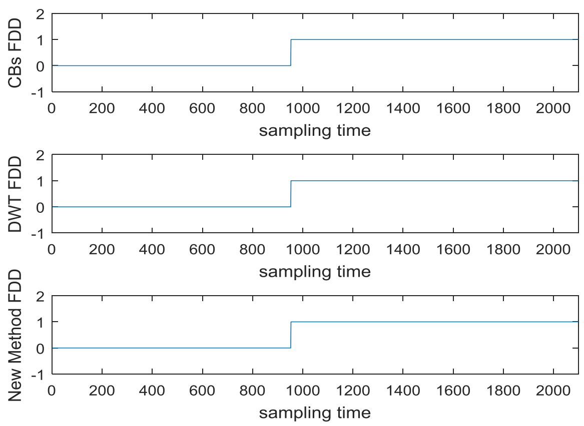

Fig. 8 Faulty signal outputs of CBs, DWT, and new FDD technique.

- **Noisy Signal**

The second noisy signal division is assessed. Fig. 9 shows a kind of noise, for instance, phase A voltage surge at 722 sampling moment on bus 3 and related to DWT. From this figure this noise is shown as a blame or defective signal where there is a fluctuation occurring at CD_1 for this bus, this output pronounced that when commotion or noise occurs, DWT is not favored. The DWT does not distinguish between defective and noisy signals and performs a comparable action. In any case, our new technique has the ability to distinguish between them, and when the signal is noisy, the system structure keeps its ordinary activity as showed in Fig. 10.

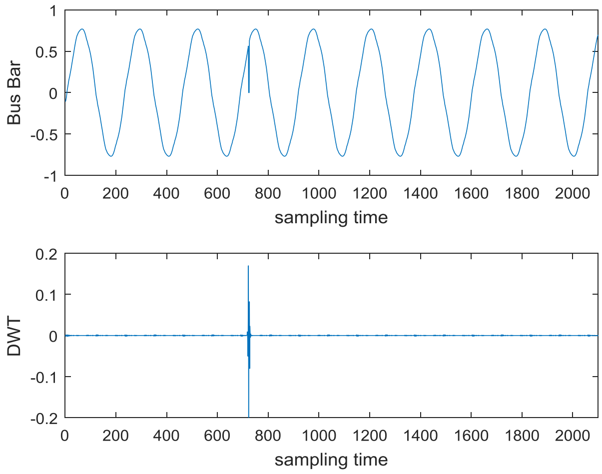

Fig. 9 Noisy signal and DWT.

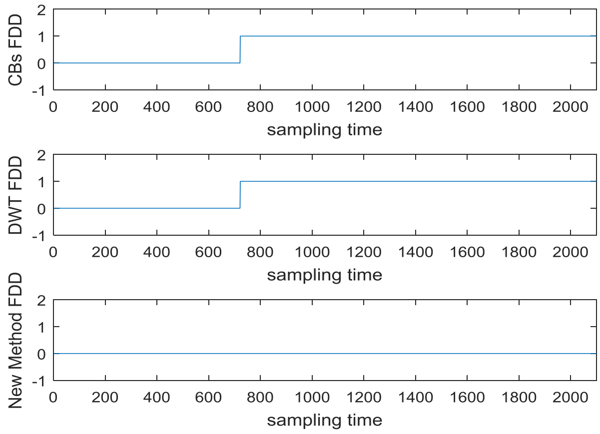

Fig. 10 CB, DWT, and new method FDD output for noisy signal.

V. CONCLUSION

This paper has provided a more precise FDD technique that can be used to differentiate between faulty and noisy signals on any smart grid, as well as all preparations, preliminaries and experiments on the standard IEEE 14 bus system. A decision Tree classifier was ready to achieve this goal based on various power system errors depending on the weight of energy collected from any signal. The proposed technique and DWT were examined in order to test the proposed approach, the proposed technique is found to outperform DWT in two points, first, its fault area recognition velocity as there is no delay time for detecting the fault. Second, the classifier can discriminate between noisy and faulty signals.

Table- I:Subscripts

Subscripts	explanation
$a_{0,k}$	scaling functions coefficients
$CA_{1,2,3,...}$	Coefficients of approximation$_{1,2,3,...}$
CB	Circuit breakers
$CD_{1,2,3,...}$	Coefficients of details$_{1,2,3,...}$
FDD	Fault detection diagnosis
$d_{n,k}$	wavelet coefficients
db4	Daubechies mother wavelet (length of four)
DWT	Discrete Wavelet transform

y (x)	signal
GPS	Global positioning system
φ (t)	scaling function
MRA	Multi resolution analysis
k	translation
n	dilation
PMU	Phasor measurement unit
ψ (t)	orthogonal wavelets
Pu	per unit

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