Enhanced Fault Diagnostic Technique Applied to IEEE 14-bus Smart Grid Standard

Ghada M. Amer, Ayman S. Selmy, Wael A. Mohamed

Abstract: Due to the gigantic power quality (PQ) demands for modern systems, power systems fault detection and diagnosis have become a significant issue. For this aim, it's very important to detect the fault at early time and determine its location through any signal. Several methods and techniques are applied to solve this problem such as discrete wavelet transform (DWT). Although DWT has the ability of fast time detection of the fault, it has a problem to discriminate between faulty and noisy signals.

DWT succeeds to extract features from altered transient disturbances, but it fails to differentiate between transient disturbances due to healthy or noisy signals. Fusion between DWT for its speed and radial basis function for its accuracy is done. The fusion technique used has a major disadvantage of its delay time as the fault can be detected after the exact location with several samples.

In this paper new technique will be proposed to overcome the DWT and data fusion method problems, to achieve the classification between noisy and faulty signals with high accuracy. The proposed method is executed to classify the signals premised on weights of them, complex tree classifier uses the energy of the signal as a feature. All simulations are achieved and done on IEEE standard 14 bus system to confirm the ability and capacity of new suggested technique. Simulation results show a better performance of the proposed system in comparison with other methods, and that it capable to differentiate between faulty and noisy signals and precisely locate the fault position.

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

I. INTRODUCTION

To keep the reliability and validity of power suppliers, and performing the analysis of fault, diagnosing and detecting the faulty locations at early time are very important at power grids [1]. In addition, as soon as the occurrence of fault in power grids, such as short circuit, it could quickly spread and propagate in all parts of the distributed system and secondary faults might be caused in power system. Old methodology to diagnose the fault was established on data from protection elements such as circuit breakers and different relays is regularly ineffective and incompetent owing to effect of the fault scattering and doubt in all parts of power system [2].

Thus, the integration of continuous voltage and discrete data gained from the circuit breakers are necessary to develop the capability of fault diagnosis and detection in the smart grids [3], [4].

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The diagnosis and detection of fault have become extensively believe in power grids, data from Phasor measurement unit (PMU) is used to locate the fault index of smart grids [5], [6], [7].Voltages and currents are determined by using PMU which receipts synchronization signals from global positioning system (GPS) satellites [8]. And because that; the measurements of PMU are actual excessive [5] and it is not favorable to connect them at everywhere in the power grid, so; it is widespread to use minimum number of PMUs and compute voltage at all nodes of different grids using the most common relation as Ohm formula [6]. Numerous data from altered sources to the structure of database creates a wealthy databank which is further consistent and reliable than discrete sources, this is owing to the integral assets of the methods of data fusion, and the results are suitable and proper in an occasion of imperfect data. In recent times, the data fusion techniques have been broadly used in other areas where it can improve the process of decision making where multiple information is available from altered sources [9].

The new technique presented in this paper give a consistent result compared with other fusion methods [10]. The main originality of this paper is the way which gain improved results compared with other techniques. In power system, the CBs information is not trustworthy owing to a rapid dispersal of the fault which trips more than one of the CB in the system when the occurrence of fault. Therefore; numerous CBs frequently respond with fault depend on seriousness of fault where detecting exact fault location is very hard. The suggested method identifies and detects the fault location based on energy of each signal where the complex tree classifier determines the signal is faulty or not, then if the signal is faulty the new technique identifies its exact location. 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. THE THEORETICAL BACKGROUND OF THE COMPONENTS OF PROPOSED METHOD

The discrete wavelet transform, classification learner tool and complex tree method will be illustrated and explained. To check the proposed system accuracy, comparison will be made between DWT and proposed method.

A. Discrete Wavelet Transform (DWT)

DWT of a signal is equal to transmitting the signal concurrently through a sequence of low pass and high pass filters.

Not only does it have an oscillating wave like characteristic, it also has the capacity to allow concurrent assessment of moment and frequency with a flexible mathematical basis. Wavelet analysis is comparable to the analysis of Fourier in the sense that it breaks down a signal for analysis into its constituent components. While the Fourier transforms the signal into a series of different frequency sine waves, the wavelet transforms the signal into its "wavelets," scaled and shifted versions of the "mother wavelet. The dilation function of the discrete wavelet transformation can be portrayed as a tree of low and high pass filters with each stage transforming the low pass filter as shown in Figure 1. [11]

The initial signal is subsequently decomposed into lower-resolution parts, with no further analysis of the high-frequency parts. The maximum amount of dilations that can be done depends on the input size of the information to be analyzed, with 2N information samples allowing the breakdown of the signal into N discrete concentrations using the discrete wavelet transformation.

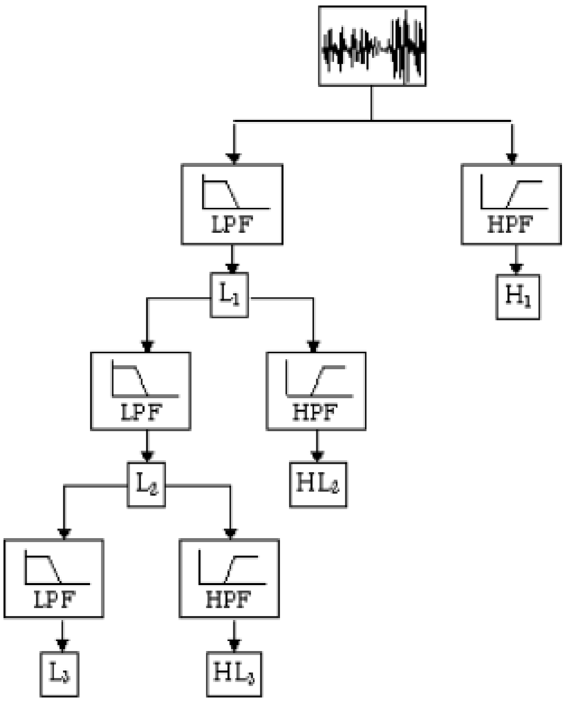

Fig. 1. Representation filter bank of DWT dilations [11].

The orthogonal property and previous properties create them to be suitable for monitoring signals and faults diagnosis [12]. The signal can be displayed by using a collection between wavelet decomposition and scaling functions at variant locations (positions) and scales (durations) [12], [13].

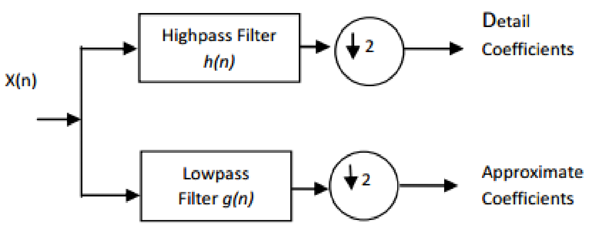

Fig. 2. Decomposition of single stage DWT [14].

As shown in figure 2, the low pass and high pass filter outputs are depicted respectively by coefficient of approximation and coefficients of detail. The low-pass and high-pass filter outputs sub sampled for the x[n] input signal is provided by [14]:

$$y_{low}[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n-k] \qquad (1)$$

$$y_{high}[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n-k] \qquad (2)$$

Only half the input signal frequency band is connected with output and half of each filter output characterizes the signal. This decomposition results in two- fold resolution of the frequency and half- time. Using low- pass and high- pass filters, frequency resolution and down sampling can be further improved by repeating the decomposition cycle. This low- pass and high- pass filter bank that breaks down the input signal is called the filter bank for evaluation. Another filter bank, called the synthesis filter bank, performs the inverse DWT by mixing sub-band signals to give the signal x[n]. To meet the perfect condition of reconstruction, $\hat{x}[n]$ should be equal to x[n]. [14].

B. Classification

Classification is one category of supervised machine learning where an algorithm “comprehends “to classify 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.

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, logistic regression, discriminant analysis, ensemble, and nearest neighbor’s classification. The classification used at suggested method are complex tree.

C. Complex Tree

Choosing a classification algorithm is usually based on a number of variables, including software accessibility, ease of use, and efficiency, which are measured by general classification precision. The maximum likelihood (ML) method is the algorithm of choice for many customers due to its ready accessibility and the fact that an expanded training process is not required. Researchers are now widely using artificial neural networks (ANNs), but their operational apps do not allow the user to specify the setup of the network architecture and provide values for a number of parameters, both of which affect performance. The ANN also needs an expanded stage of training. The use of decision trees (DTs) to classify remote sensed information has risen over the previous few years. The method's proponents argue it has a number of benefits 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 easily accessible on the Internet to implement DTs. Pruning DTs can make them smaller and easier to interpret, while using boosting methods can enhance efficiency [15].

III. THE METHOD DESIGN AND STRUCTURE CRITERIA

The design criteria of the proposed technique will be demonstrated in this section by explaining the suggested fault diagnostic unit based on discrete wavelet transform, also applying the framework of the proposed new technique to detect the fault at each defective or noisy signal.

A. The proposed DWT-based fault diagnostic unit

Due to the orthogonal and locality of the fundamental features, discrete wavelets transform is confirmed as a powerful technique for evaluating non-stationary signals [16], [17]. These fundamental features are recognized as wavelets of the mom. Daubechies, and Haar are two popular mother wavelets. The fault detection goal is decomposed by MRA method to understand the information and approximation of the defective signal at different levels. For Daubechies mom wavelet with a length of four (db_4), Fig. 3 shows a defective signal and its decomposition levels. The horizontal axis is the sampling time and the cephalic axis is graded per unit. It is shown that the coefficient of detail1 (CD_1) includes the high frequency signal and exposes rapid modifications in the defective signal and may be used to identify the fault time. It also indicates that a fault or the impact of the fault may happen in places on buses where the value of CD_1 is important. 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 mentioned with actual figures in the coming sections.

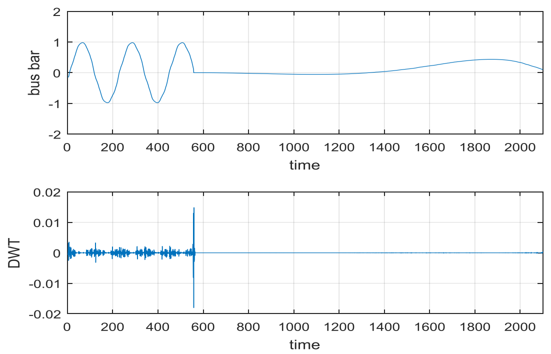

Fig. 3. A faulty signal for db4 wavelet and its level of decomposition.

B. The structure of the proposed new method

In this section a novel technique for diagnosing the place and moment of the fault in the IEEE standard 14 bus scheme will be presented. To this end, the model makes some activities gradually as shown in the below flowchart in figure 4, first calculates the energy of the unknown signal, then the fresh model suggested checks whether the signal is defective or not based on a learner classifier that practiced on more specific defective signals in all areas of it. And if the status is defective, the proposed technique will attempt to figure out where the fault occurs at any bus bar in relation to the fault index according to the signal variance. Where the peak variance shows the fault index for all units, the comparison between all these values to get the maximum specifies the defective bus, but if the situation is a "noisy signal," no fault will be identified depending on the learner classifier's choice.

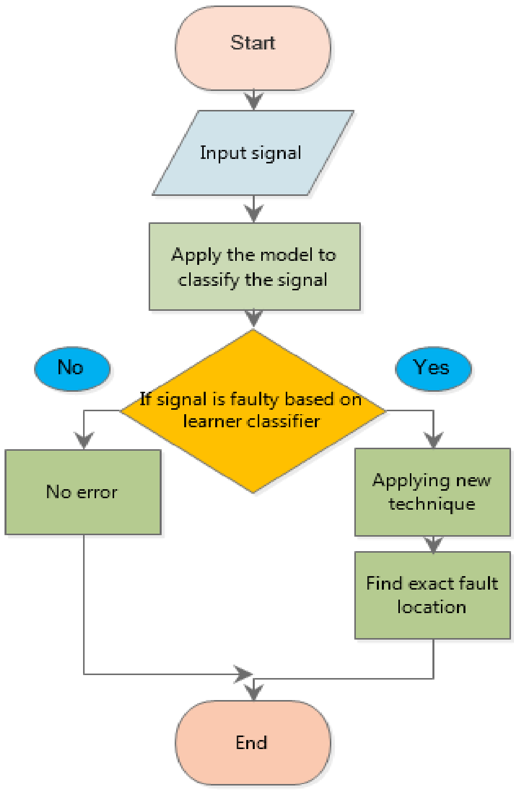

Fig. 4. The structure of proposed method.

IV. SIMULATION STUDIES AND RESULTS

The proposed technique to the fault detection and location is applied to the IEEE standard 14 bus scheme as shown in figure 5. According to the suggested model, fault scenarios on this scheme are as follows when testing to check the efficiency of FDD systems. This system is used as one of the main power systems, this power system is widely used as a case study due to its sensible complexity and structural matching compared to micro grids [18]. To test the reliability and consistency of the proposed model, several faults are introduced into the system at different bus locations.

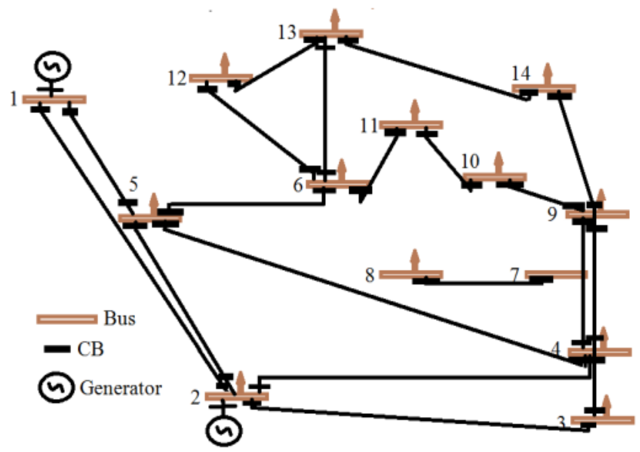

Fig. 5. IEEE standard 14 bus system [10].

The suggested technique would apply to different types of faults that may occur as follows on power grids:

A. Phase to ground fault

Figure 6 shows the sampling time on bus 3 and its respective DWT where the ground fault stage happens at the 557-sample index. Bus 4, the closest to bus 3, has a large impact. In traditional systems, the CBs senses fault through any power system at a premature stage, but they can't detect the specific fault place whereas near-fault buses can be impacted more than far-off buses. The two CBs of bus 3 and bus 4 have the action of tripping due to the severe fault at the 557-sampling time. Fig. 7 shows the defective signal of bus 4 and it's DWT. The output of DWT shows signal differences where in bus 3 the CD_1 value shifts from nearly nil to 0.0149 Pu at 559 sampling time, while in bus 4 the corresponding value increases as the highest value to 0.0034 Pu. DWT output shows signal differences where in bus 3 the CD_1 value shifts from nearly nil to 0.0149 Pu at 559 sampling time, while in bus 4 the corresponding value increases as the highest value to 0.0034 Pu. The high-level noisy scheme, though, can declare a defective signal to be discovered by the DWT. Since CD_1 holds a peak frequency signal like a noisy signal. Therefore, FDD can't use DWT alone, but can be used with any fusion method or with the proposed technique created in this document. Fig. 8 displays the production of the suggested CBs, DWT and fresh technique. As shown in Fig. 8 the DWT technique identifies the defective signal at bus 3 at the sample index of 559. Suggested new technique also detects defective signal at bus 3 at the sample index of 557. The proposed technique is used to improve fault identification. Where delay time is lowered, efficiency in identifying the fault place is improved, however, the newly established technique is more accurate and quicker than DWT.

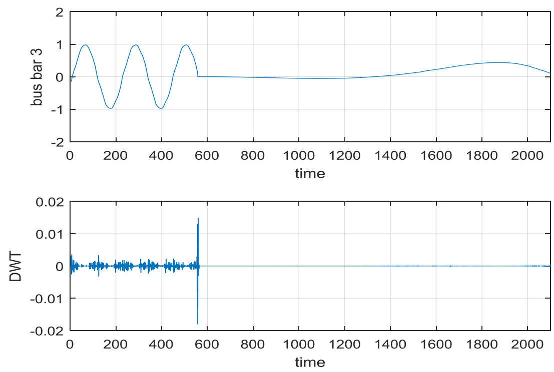

Fig. 6. Faulty bus at 557 sample index and its corresponding DWT.

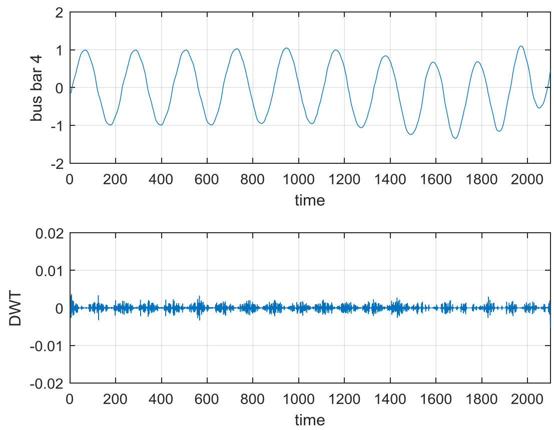

Fig. 7. Phase A on bus 4 and its corresponding DWT.

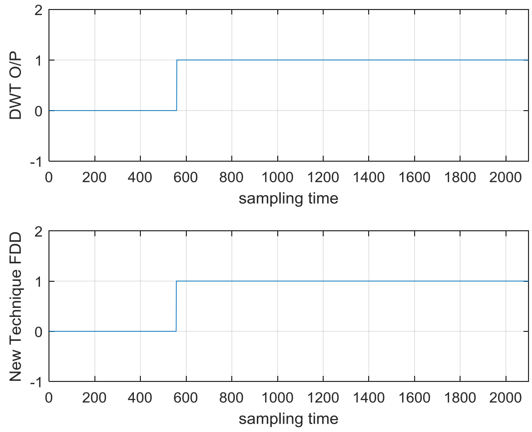

Fig. 8. Output of DWT, and new technique FDD system for faulty signal.

B. Phase to phase to ground fault

Two lines (and each other) come into contact with the ground, often commonly caused by storm damage where fault occurred at sample index 933 as shown in the next figure.

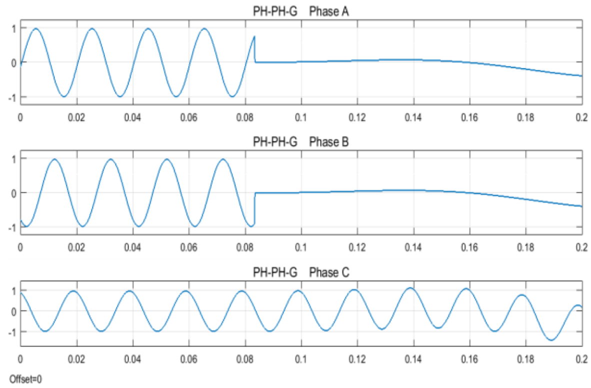

Fig. 9. Phase to phase to ground fault signals.

Each of the proposed technique and DWT system are applied on this system to detect the fault location where the faulty bus is located at bus 3 exactly with sampling time 933 and 934 for proposed data fusion technique and DWT respectively as shown in next figure.

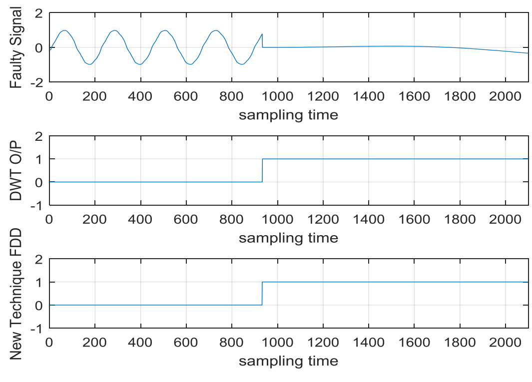

Fig. 10. Output of new method FDD system for phase to phase to ground fault.

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In case of phase to phase to phase to ground fault each of the three phases is equally affected by a symmetrical or balanced fault. If this faults arise, it do very serious damage to the machinery, even if the system remains in a balanced state.

Each of the proposed technique and DWT system are applied on this system to detect the fault location where the faulty bus is located at bus 3 exactly with the same sampling time as showed in fig. 10.

Also Phase to phase fault is executed on DWT and proposed technique and gives the same results.

C. Voltage sag (voltage dip)

It is a faulty-term voltage drop that can be induced by overloaded machines, a short circuit, or start of electric motors. The starting fault location occurred at sample index 600. The DWT is applied on this system were fault bus 3 is detected with sample index 601 is located as in next figure.

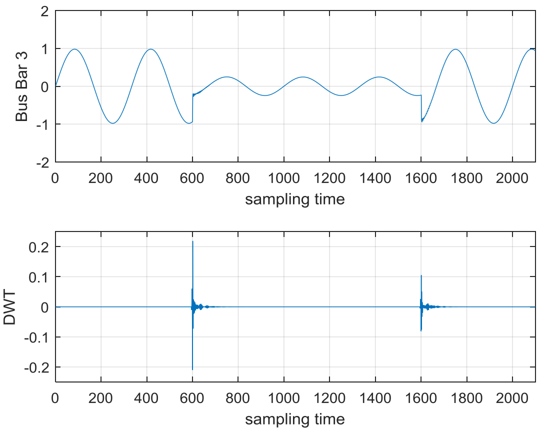

Fig. 11. Phase A on bus 3 and its corresponding DWT.

The proposed technique is applied on this system to detect the fault location where the faulty bus is located at bus 3 accurately with sampling time 600 as shown in next figure.

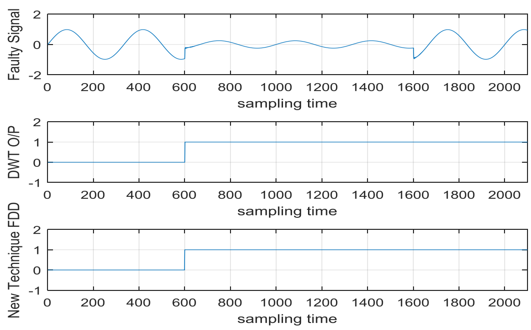

Fig. 12. Output of new method FDD system for Voltage sag fault.

D. Voltage swell

It's the voltage sag's reverse. The voltage swell, which is a momentary voltage spike, happens when a large load in a power system is turned off. The beginning of fault occurred at sample index 701.

The DWT is applied on this system were fault bus 3 is detected with sample index 702 is located, also the proposed data fusion technique is applied on this system to detect the fault location where the faulty bus is located at bus 3 precisely with sampling time 701 as shown in next figure.

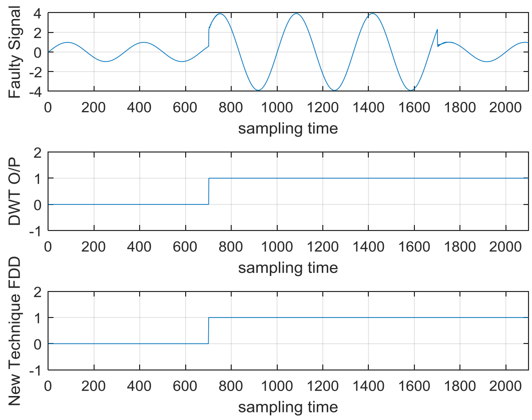

Fig. 13. Output of new method FDD system for Voltage swell fault.

E. Noisy Signal

This section for a type of noise such as voltage spike on phase A at 620 sampling time on bus 3 and its corresponding DWT. It is indicated from Figure 14 that this noise considered as a fault where there is a variance occurred at CD_1 for this bus, this output declared that DWT isn't preferred when noise exists. The DWT doesn't discriminate between noisy and faulty signals and takes the same action. But our new method has the capability to distinguish between them and when the signal is noisy the system keeps its normal action as mentioned at Fig. 14 and Fig. 15.

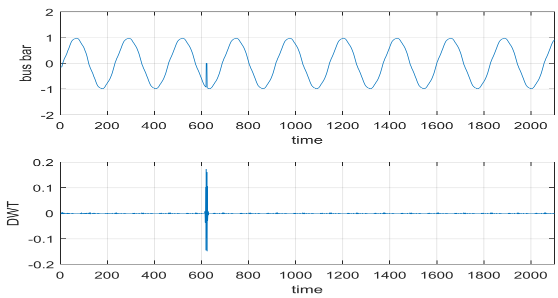

Fig. 14. Noisy signal and its DWT.

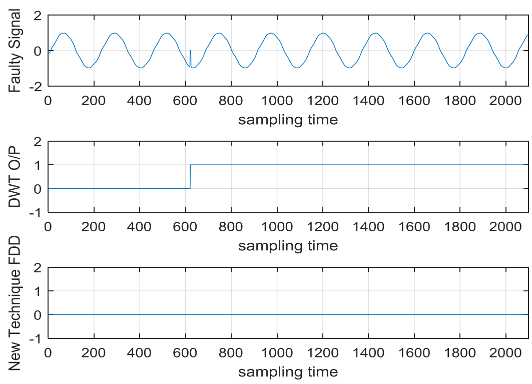

Fig. 15. CB, DWT, and new method FDD output for noisy signal.

V. CONCLUSION

This paper presented a reliable FDD method that can be used to define the location and fault index on any smart grid, all new technique training, experiments and tests are performed and executed on the

IEEE standard 14 bus scheme. For achieving this objective, the classifier calculates the energy of any unknown signal, then the new proposed model checks whether the signal is faulty or not based on a learner classifier that used more particular faulty signals in completely fields of the signal. To test the suggested method, a comparison was made between the suggested scheme and DWT, it is discovered that the suggested methods outperform DWT in two points, first, its detection speed of fault location. Second, the classifier can discriminate between defective and noisy signals.

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Table- I: Subscripts

General terms	explanation
ANNs	artificial neural networks
CBs	Circuit breakers
CD	Coefficients of details
DTs	decision trees
db4	Daubechies mother wavelet (length of four)
DWT	Discrete Wavelet transform
GPS	Global positioning system
ML	maximum likelihood
MRA	Multi resolution analysis
PMU	Phasor measurement unit
PQ	power quality
Pu	per unit

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