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Electrical Engineering Department

Improved Data Fusion Technique for Optimal Design and Operation of Fault Detection Systems

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By

Eng. Ayman Soliman Selmy Mohamed

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Under the Supervision of

Prof. Dr. Ghada Mohamed Amer
Department of Electrical Engineering
Benha Faculty of Engineering
Benha University

Assoc. Prof. Wael Abdel-Rahman Mohamed
Department of Electrical Engineering
Benha Faculty of Engineering
Benha University

Benha University
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The undersigned have examined the thesis entitled **"Improved Data Fusion Technique for Optimal Design and Operation of Fault Detection Systems"** presented by Eng. Ayman Soliman Selmy Mohamed, a candidate for the degree of Doctor of Philosophy in Engineering Sciences in Electrical Engineering and hereby certify that it is worthy of acceptance.

Approved by the Examining Committee:

Prof. Dr. Rizk Mohamed El-sayed Hamouda Faculty of Engineering , Ain-Shams University. Dean of the Canadian Higher Institute of Engineering, 6th of October.	**(Exterior Examiner and Committee Chairperson)** .....
Prof. Dr. Mohamed EL-Shimy Mahmoud Bekhet Faculty of Engineering Ain-Shams University.	**(Exterior Examiner)** .....
Prof. Dr. Ghada Mohamed Amer Benha Faculty of Engineering, Benha University.	**(Thesis Main Advisor and Examiner)** .....
Accepted for Electrical Engineering Department **Prof. Dr. Ayman Ali Ahmed Nada**	**(Department Chairman)** .....
Accepted for the Postgraduate Affairs: **Prof. Dr. Ghada Mohamed Amer**	**(Vice Dean for Post Graduate Studies)** .....
Accepted for the Faculty: **Prof. Dr. Aref Mohamed Ahmed Soliman**	**(Dean of the Faculty)** .....

ABSTRACT

This study presents a new technique for fault detecting and diagnosing (FDD) of power grids faults. Data fusion topologies are a popular practice in smart grids, offering the opportunity to fuse data to gain a new feature dependent on the complementary sensors. In fact, to gain a forecast dependent on certain detectors, likely in certain regions, when another detector failures. Related to prior measurements, associated sensors can achieve the above capabilities. The whole thesis presents the issue of finding an enhanced data fusion methodology used for optimal design and operation of fault detection systems.

Discrete Wavelet transform (DWT) has a major drawback 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 will be execute to provide a more reliable and accurate decision to determine the exact location of the fault. In this technique, the complex tree 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.

In comparison, the presented technique has been extended to several study cases such as faulty or noisy signals to show the effectiveness of the enhanced methodology.

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.

List of Published Papers

The thesis is relied upon the analysis mentioned in the papers below:

1. G. M. Amer, A. S. Selmy, and W. A. Mohamed, “Improved Technique to Diagnose Fault in IEEE Standard 14-Bus System”, *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*, Vol. 9, No. 2, pp. 2819-2824, 2019.

2. G. M. Amer, A. S. Selmy, and W. A. Mohamed, "Enhanced Fault Diagnostic Technique Applied to IEEE 14-bus Smart Grid Standard", *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*, Vol. 9, No. 4, pp. 1825-1830, 2020.

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LIST OF MAIN SYMBOLES AND ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
CB	Circuit Breaker
$CD_{1, 2, 3...}$	Coefficients of $Details_{1, 2, 3...}$
DAI-DAO	Data In-Data Out
DAI-FEO	Data In-Feature Out
Db_4	Daubechies Mother Wavelet (Length of Four)
DEI-DEO	Decision In-Decision Out
DF	Data Fusion
DFT	Discrete Fourier Transform
DOD	Department Of Defense
DWT	Discrete Wavelet Transform
EMD	Empirical Mode Decomposition
FCDFT	Full-Cycle Discrete Fourier Transform
FDD	Fault Detection Diagnosis
FEI-DEO	Feature In-Decision Out
FEI-FEO	Feature In-Feature Out
FFT	Fast Fourier Transform
FL	Fuzzy Logic
GPS	Global Positioning System
HCDFT	Half-Cycle Discrete Fourier Transform
HCI	Human Computer Interaction
HST	Hyperbolic S-Transform
HT	Hilbert Transform
IEDs	Intelligent Electronic Devices
IMF	Intrinsic Mode Functions
ITD	Intrinsic Time Decomposition
JDL	Joint Directors of The Laboratories
NN	Neural Network
PMU	Phasor Measurement Unit
PNN	Probability Neural Network
PQ	Power Quality
PRCs	Proper Rotation Components

Pu	Per Unit
QSSVM	Quarter-Sphere Support Vector Machine
RBFNN	Radial-Based Function Neural Network
RMS	Root Mean Square Value
S_n	Sensor Number n
ST	S-Transform
STFT	Short Time Fourier Transform
SVD	Singular Value Decomposition
SVM	Support Vector Machine
WMRA	Wavelet Multi-Resolution Analysis
WT	Wavelet Transform

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CHAPTER 1

CHAPTER 1

INTRODUCTION

1.1 Overview

Networks of power systems may involve a large number of substations, each generating very large outputs. The electric power network may be categorized to three major components as shown in next figure:

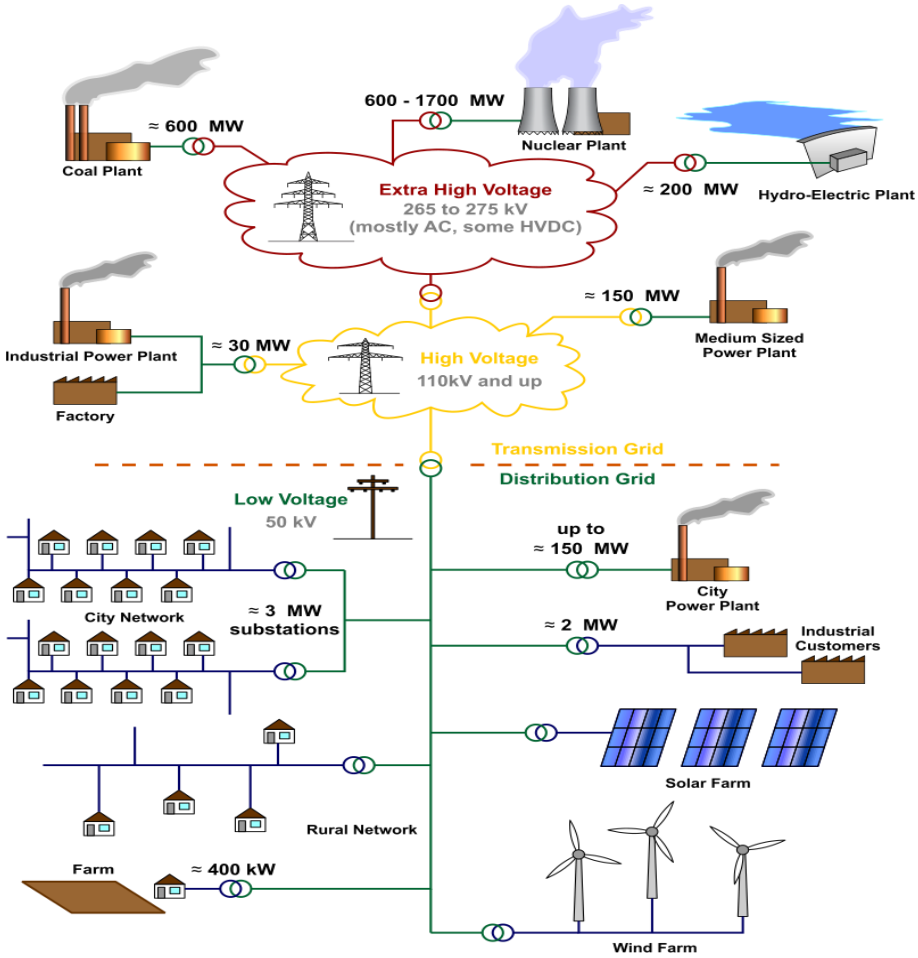


Fig. 1.1. Electric power network components

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]. Due to the gigantic power quality (PQ) demands for modern systems, power systems fault detection and diagnosis have become a significant issue. 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 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]. The diagnosis and detection of fault have become extensively believe in power grids, information 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 calculate 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 thesis gives a consistent result compared with other fusion methods [10]. 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 voltage and power 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.

1.2 Thesis Objectives and Contributions

The main objectives of this thesis are:

1- A new technique for fault detecting and diagnosing of power grids faults is presented.
2- A major drawback of Discrete Wavelet transform (DWT) such as noise sensitivity is discussed.
3- A high precision classification of noisy and faulty signals could be obtained. and Finally,
4- Suggestion of algorithm used to find a more reliable and accurate decision to determine the exact location of faults.

The main Contributions of this thesis are:

1- Using hybrid fusion system.
2- Enhanced the performance of fusion systems.
3- Making a robust system to differentiate between noisy and faulty signals.

1.3 Thesis Outlines

The main aim of this study is to identify the location for smart grid faults and to distinguish between noisy and faulty signals. To test the reliability and accuracy of the proposed methodology, all simulations were done and performed on the standard IEEE 14 bus system. The following are the details of the thesis outlines:

Chapter 1: An overview to thesis work is presented. The main objectives and contributions of the thesis are introduced. Finally, Thesis outlines are showed.

Chapter 2: This chapter contains an overview of the methods that discussing the determination of fault location at power grids. Also the flow chart for proposed technique is presented. The strategies used were based on three methods such as (time domain – frequency domain – time and frequency domain), then fault classification algorithms reported in power grids will be divided into four categories (conventional methods - Smart / artificial intelligence methods - hybrid Strategies – logic flow methods).

Chapter 3: This chapter deals with the data fusion techniques and collect the literature survey for prior studies in this field. The approaches and procedures used can be listed as follows:

- Assisting with input / output data types and nature.
- Based on the relation between the sources of inputs.
- Established on type of architecture
- Derived from various degrees of data fusion discussed through JDL

Chapter 4: This chapter contains simulation studies and results where symmetric and asymmetric faults will be presented. Faults between

phases and ground with their various types will be discussed. Voltage sag and voltage swell will be implemented. Lastly, the noisy signal with its effects on the power grid is explained, and finally,

Chapter 5: In this chapter the conclusions and probable future work for this study are offered.

CHAPTER 2

CHAPTER 2

LITERATURE SURVEY

2.1 Introduction

Fault detection diagnosis (FDD) techniques that can be used to detect accurately the fault and also differentiate between faulty and noisy signals are very important at any smart grid [11]. Identification of faults (detection, classification, and determination of fault location) is the most important activity used in the safe relaying power stations [12]. The malfunctioning of protective relay systems capable of detecting, diagnosing, distinguishing defective phases and avoid fault influences during the time of fault can have negative impacts on power grid systems. Thus, the method of fault detection should be done correctly as rapidly as possible for declining the duration abrupt and facilitate the return of electric service. The fault detection, classification, and determination of fault location are essential parts in the process of identifying faults. Hence, these roles must be included in the safe relaying of power transmission to improve the overall stability of the power grid.

Fault identification techniques meet multiple problems including signal processing issues. For last decades have seen the growing involvement in the discovery of power system faults in various scopes. In addition, the effect of diverse and varying network topologies may present several issues related to algorithms for detecting faults. Recently sophisticated intelligent electronic devices (IEDs) were introduced and implemented to mitigate these problems to collect distinct details in power plants at several buses (nodes) [13].

Within this chapter, a comprehensive survey of the literature on the studies implemented within algorithms of fault identification is viewed.

2.2 Detection, Classification, and Determination of Faults

Overall, such detailed review is graded based on the current following three main components:

- Detection of fault.
- Classification of fault (faulty or noisy signal).
- Determination of fault location (in case of faulty signal only).

2.2.1 Detection of fault

It's well recognized whenever at time of fault happens, the electrical signals such as (current, voltage, and power) produce important knowledge, that is also extracted which is used in algorithms for detection of faults. Appropriately, feature extraction method of the function was commonly used to obtain identifiable features of faulty signals as well as to decrease the dimension of input vector of data.

Current techniques for detection the faults can also be classified according to the extraction methods used. While the key issue for many research scientists is to establish an effectiveness technique of extracting valuable features for issues in fault detection. Feature extraction methods can be categorized as follows in various domains:-

- Time domain
- Frequency domain
- Time and frequency domain

I. Detection of fault built on Time domain strategies

Time domain strategies for the Empirical Mode Decomposition (EMD) techniques focused on fault detection have been provided as in [14-19]. This approach was commonly used for the study of nonlinear and non-stationary signals in power system studies. Reference [14] interacted with a research analysis of the general theory of the EMD methodology. Essentially, it is a sifting process where different oscillation modes are extracted from the initial signal. Hence these modes obtained are mono-component signal like limited frequency band. So the EMD is a technique that can be represented as intrinsic mode functions (IMF) to decompose the specific signal into the set of orthogonal elements. The IMF is characterized as just an oscillating function, reflecting the dynamics on various time-scale characteristics. This will also fulfill two conditions as follows:

- The average value of the higher and lower envelopes is null at every point.
- It only has about one maximum in between zero crossing points for a data set.

Study of the time series estimated by the algorithm in [15] combined wavelet transform and empirical mode dependent on decomposition. With wavelet transform, the original time signal and IMF are decomposed. The results obtained from this study showed that this approach would decompose strongly non-stationary and non-linear signals into physical representative IMFs.

References [16, 17] merged Hilbert Transform (HT) with EMD technique to find faults in transmission networks. In [16], EMD integrated with HT was developed on transmission lines for detection of faults. Reference [17] provided fault detection technique using EMD and HT for decomposing any faulty signal into the instantaneous

amplitudes and frequencies. If a fault happens, the instantaneous amplitudes and frequencies become drastically modified, and the researcher picked them as features of a discriminative fault.

Reference [18] measured the efficiency of WT and the detection of disturbance based on EMD on transmission lines. The authors noticed that EMD approach had improved performance for identifying faults.

A new technique for detecting faults in power grids depending on the Intrinsic Time Decomposition (ITD) approach was introduced in the algorithm discussed in reference [19]. The ITD is a rapid time-domain signal processing method that doesn't require sensible tuning variables. And after that, the Singular Value Decomposition (SVD) methods used to decompose the Proper Rotation Components (PRCs) based ITD matrix of the currents obtained from the single-terminal of the secured phase.

II. Detection of fault built on frequency domain strategies

The frequency domain techniques may be commonly used to study transient signal, offering actual precise data on the frequency quality of the transient signals. it is common knowledge that, when a fault occurs, the frequency properties of current and voltage will change dramatically across varying frequency ranges [20]. Therefore, a variety of methods used to analyze frequency properties of time-domain signals.

The commonly mathematical technique used is Discrete Fourier Transform (DFT) for digital systems that allows one to find the spectrum of time-domain signals. In addition, rapid execution of DFT could be completed utilizing Fast Fourier Transform (FFT) mechanism. FFT technique is used to convert discrete-time data sets into a discrete-frequency representation [21]. At reference [22], the authors noticed that the efficiency of full-cycle (FCDFT) and half-cycle (HCDFT)

techniques can be considered relatively similar towards each other. At reference [23] addressed with two techniques of removing harmonics and weakening DC elements using DFT strategies of full and half-cycle. In comparison, HCDFT velocity is faster than FCDFT. Hence, people uses HCDFT during fault occurrence to measure the symmetric component. Similarly, the necessity for HCDFT for fault determination was presented in [24, 25]. The detecting of fault for transmission line in [26] was indicated by evaluating phase voltage range using FFT method. References [27, 28] implemented FCDFT based approaches for purposes of data protection. The authors in [29] used the FFT method to convert the faulty signal from time to frequency domain. Reference [30] stated that DWT 's output for a single phase to ground fault case was higher than DFT, whereas DFT has strong results for certain kinds of fault. Instead, from the transient frequency band, traveling wave frequencies have been obtained to identify and locate various forms of faults. At reference [31] built DFT to obtain the severity of essential fault currents as features for process identification of failures. Reference [32] presented an improved DFT technique for real-time, time-domain interpolation-based applications.

Since the faults are a non-stationary transient phenomena, details about different spectral components which occurs at the moment of the happening of the fault seems to be very important. Seeing as FT just provides time-domain spectrum for signals and no data as to where these spectral components looks in duration, it is therefore not an appropriate method for identifying non-stationary signals [33].

III. Detection of fault built on Time and frequency domain strategies

There are two techniques based on the Time and Frequency domain techniques: S-Transform and Discrete Wavelet Transform (DWT), which are regularly included in time and frequency domain analysis of the signal. Wavelet Transform is the supreme effective research tool used to evaluate faults of transmission line. Evaluated signals are being extracted from power systems that depend on frequency and time, that are defined as "chirp" signal (non-stationary signal).

Wavelet Transform (WT) has been considered as an alternate to a Short Time Fourier Transform (STFT). The signal in STFT is subdivided into smaller sufficient parts, whereby sections of the signal could be considered to be stationary. Contrariwise, Wavelet Multi-Resolution Analysis (WMRA) remains a good choice of DWT toolkit, it splits signal into small and wide segments at high and low frequencies respectively. WMRA's suitability for non-stationary signal processing is being declared at [34]. The WMRA methodology disintegrate original signal into components of low frequency (coefficients of approximation) as well as components of high frequency (coefficients of detail). DWT may extract those indexes from faulty signals, which have been used as discriminant feature for identifying faults [35]. Therefore, many scientists need to select which basis wavelet (that selects the filter bank characteristics) when applying the WMRA strategy. An appraisal research of various basis wavelets for detection of faults was given in [36, 37], that suggested haar, db2, bior3.9, sym3, coif5, and sym8 for the detection of faults. Reference [38] discussed the use of the multi-resolution analytical method of detecting shunt faults on power system. To measure fault conditions, the high frequency components of currents are utilized to calculate fault criteria. Instead, such

fault parameters are compared with threshold values for identifying faults in transmission line. A DWT-based method of detecting faults was introduced in [39]. Db4 was used as the mother wavelet to obtain their detail coefficients in the detection mode, using the fault detection technique. Through reference [40], the WMRA was described on a 220 KV transmission line for detection of faults. Reference [41] used db8 also as mother wavelet for identification of faults and for distinction between switching, shunt-faults, and lightning. Such a research also determined that the 3rd decomposed degree was the best appropriate degree of decomposition for identification and classification of faults. At reference [42], the DWT technique based on WMRA signal decomposition was utilized. Within that study, many mother wavelets have been assessed, and it has been promised that the db4 mother wavelet was chosen to that study. Reference [43] utilized DWT created estimated voltage and current coefficients relating to three phases to diagnose various types of faults. The analysis in [44] furthermore reported that db4 possesses a superior efficiency which provides accurate detection of the rapid transients produced by faults. The algorithm in [45] for detecting faults was presented utilizing db5 as that of the mother wavelet. In reference [46], the authors tried to introduce an extensive survey on the judicious choice of a mother wavelet for determination of faults. Ten various mother wavelets (db1 to db10) were reviewed at five decomposition levels to find the perfect mother wavelet for detection of faults. at paper [41], introduces a DWT-based fault identification system to decompose each signal from currents using biro2.2. Besides fault detection tasks, the fault index was calculated by trying to compare the fault index of different stages with the predefined threshold. For currents utilizing db4 and db6 wavelets, the WMRA in [47] has been evaluated to gain the distinctive characteristics for identifying faults.

S-Transform (ST) has been extensively shown as a comprehensive description of time-frequency content on non-stationary transitory signal. S-Transform is a slight modification of a continuous wavelet transformation which maintains the absolute phase on each component of the frequency. Reference [48] discussed a new strategy for protection based mostly on hyperbolic S-transform (HST) and the theorem of Parseval to obtain HST coefficients from the current of faulty signal. In [49, 50], ST has extensively performed numerous techniques for detection of faults in aggregation with the neural network (NN). A new variant of the traditional ST matrix called sparse S-transform was suggested in [51]. The ST-based mechanisms, therefore, deteriorate from a high computation complexity and an unsuitable capacity to provide real-time security.

2.2.2 Classification of fault (faulty or noisy signal)

Protection systems for power grids requires classification of various possible faults and the identification of faulty cycle. Both tasks are important to reduce the abruptness of time and speed up the return of electrical service. In addition, they may be used to verify the strategies of single-phase tripping and auto-reclosure techniques [52].

Precise classification of faults in power stations is unavoidable function to achieve five goals for security power system are as follows:

- Achieve better reliability and stability of the system.
- Find the faults precisely.
- Improve single-phase adaptive tripping.
- Report fault data.
- Quick and proper mechanism for tripping.

So many fault classification algorithms reported in power grids can be divided into four categories according to their techniques, as below:

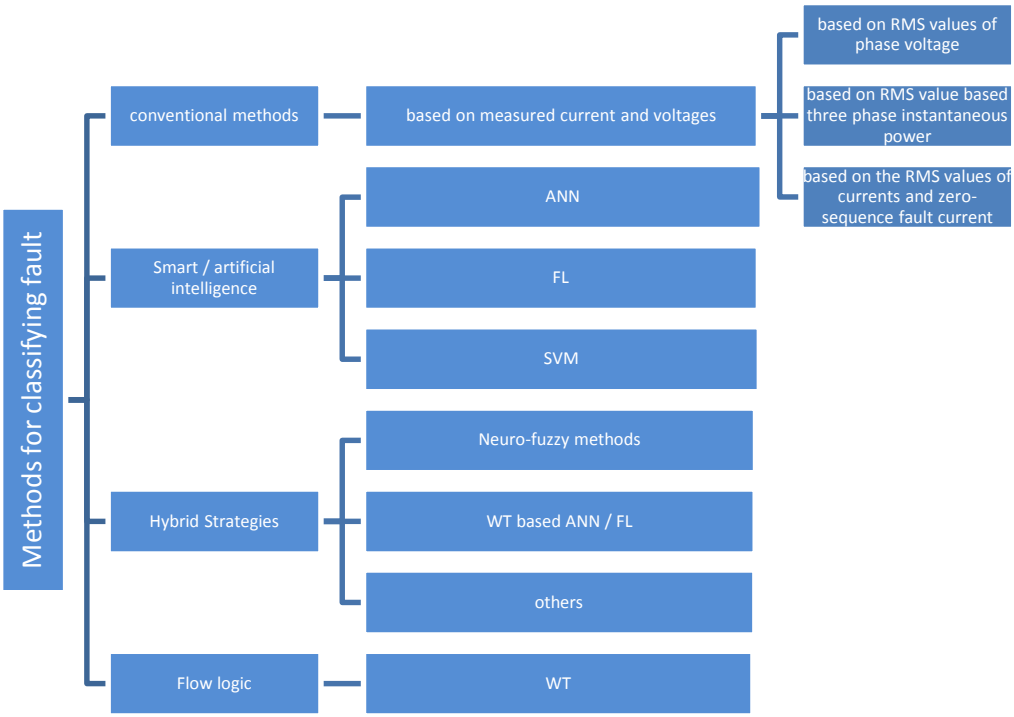


Fig. 2.1. summary of methods that is used for classification of faults in power systems.

I. Classification of fault built on conventional methods

Techniques of conventional fault classification require more complicated tasks of measured current and voltage signal. We will not however have an appropriate operation for ultra-high speed safety relays. Measured voltage and current can also be used to calculate certain quantities as distinct characteristics. In reference [53], the methodology of fault detection relied on the average square of coordinated fault current from the double end transmission line.

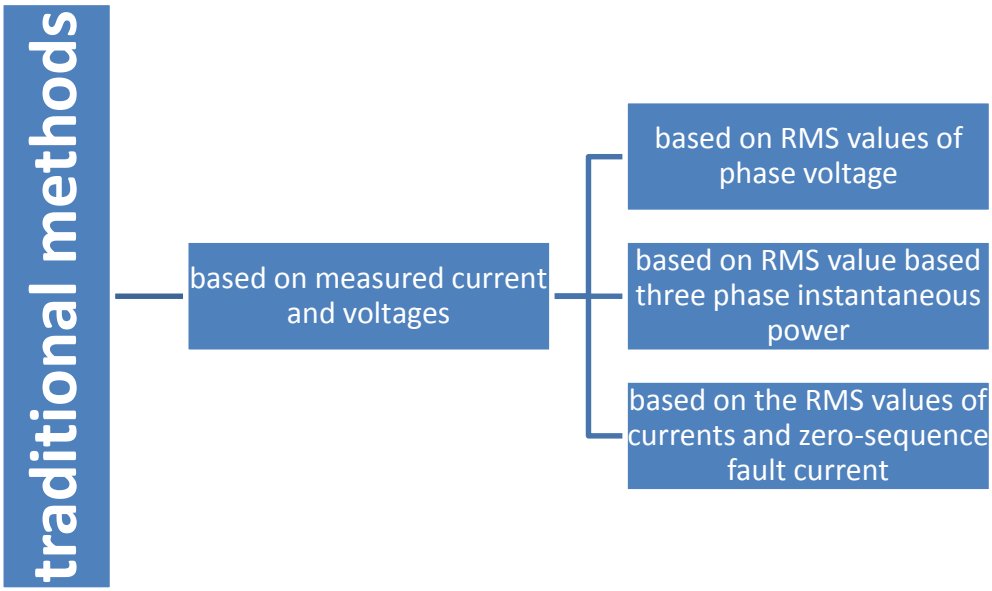


Fig. 2.2. Traditional Methods Classification

In reference [54], phase bus voltages of the measured root mean square (RMS) have been used as distinct feature to classify the faults of transmission line. The fault classification system presented in [55] relying on the RMS values of currents and the fault status of zero sequences. At reference [56], instantaneous power dependent on the three phase RMS value was measured and used in power stations for fault detection. A method for fault classification was proposed in [57] using current signal overlaid sequence components and measured apparent faulty line impedances.

II. Classification of fault built on Smart / artificial intelligence

Current structures for classification of faults are based on methods based on artificial intelligence (AI), like the artificial neural network (ANN), fuzzy logic (FL), and support vector machine (SVM).

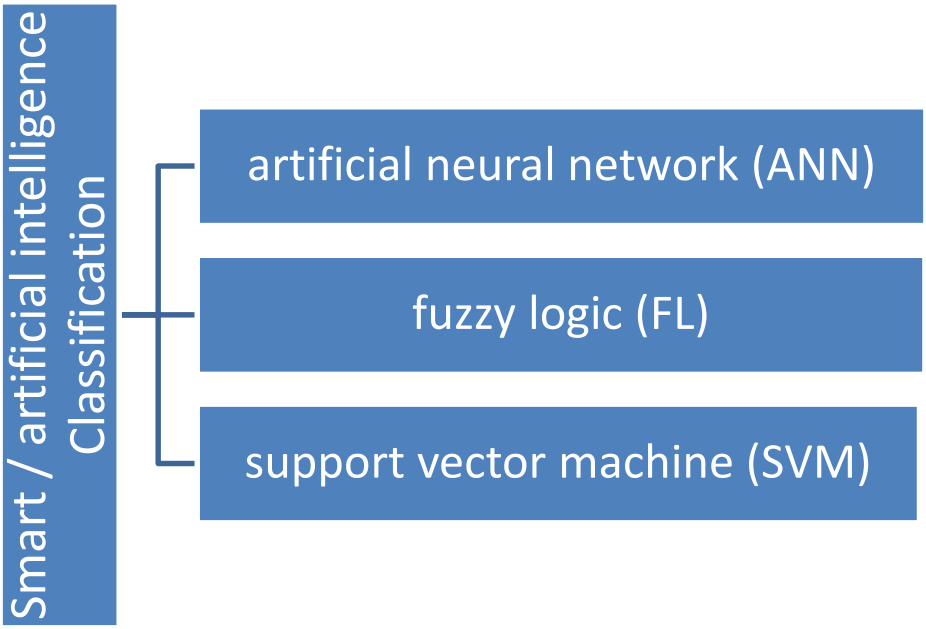


Fig. 2.3. Smart / artificial intelligence Classification

a. Techniques based on ANNs

Based on ANNs methods the fault classification strategies have already been implemented in next papers. The idea of ANNs was demonstrated in [22], and used as an alternate analytical framework to conventional approach. As input matrix, zero sequence current, damping time and amplitude have been applied to the essential voltages and current components in [58]. In reference [59] relay place sampled currents have been used as inputs then transferred to ANNs. In [60], researchers expressed a fault system for the detection algorithm for teed circuits relying on a transmission line neural network. Suggested technique was introduced in [61] to categorize faults in transmission line on double circuit transmission line. In reference [62], paper proposes classified shunt faults strategies based on ANN on tapped transmission lines. In reference [63], study identified efficient approach for the distribution system utilizing ANN-based fault classification and detection algorithm. In reference [64], the method for quick

classification of faults has been described utilizing probability neural network (PNN). After having successfully completed the ANNs-based approaches of determining the optimum type of fault, the major disadvantage to an ANN is that it needs a large amount of practice and learning.

b. Techniques based on FL

The study develops the fault classifier model in [29] relying only on the symmetric components of fault current. In reference [23], fault classification model was established mostly on angular differences between the sequence components including its basic fault current and the primary amplitudes of a phase current. The researchers offered a fuzzy set classification technique for faults in protective relay [65]. The article discussed the need for fuzzy logic method in [66] to detect and classify the nature of faults of the transmission line clearly. FL approach based on the positive and zero series current was discussed in [67] to identify and distinguish faults in transmission line.

c. Techniques built on SVM

SVM based fault classification systems have been explained in [68-74] also those strategies are being studied as fault diagnosis for protection system area. In reference [68], the study suggested a post-fault approach based on SVM fault classification methods, at which the input to a SVM is the calculated current. In references [69, 70], within that analysis, the SVM was studied for the classification of shunt faults through their frequency range. In [71], throughout this research, the SVM was studied to identify the shunt faults in series compensated power system utilizing zero sequence currents and three phase. The article presents an extensive analysis on the use of SVM and ANN for classification of faults in [72]. In reference [73], the method for fault classification with voltage and current transients throughout three terminal power lines using SVM-ANN has been presented. In reference

[74], researchers introduced two new strategies relying on one-class Quarter-Sphere Support Vector Machine (QSSVM) for the identification and classification of faults in power grids.

III. Classification of fault built on hybrid Strategies

The combination of more than one technique such as WT, ANN, FL approach and others can be defined as hybrid methods. The combination of both methods means that the deficiencies of one method used during its implementation are solved. Integrated techniques were reviewed, as Wavelet with Artificial Nero-Network [12,26,43,44,75, 76,77] and Wavelet with FL [78,79,81], neuro-fuzzy [80].

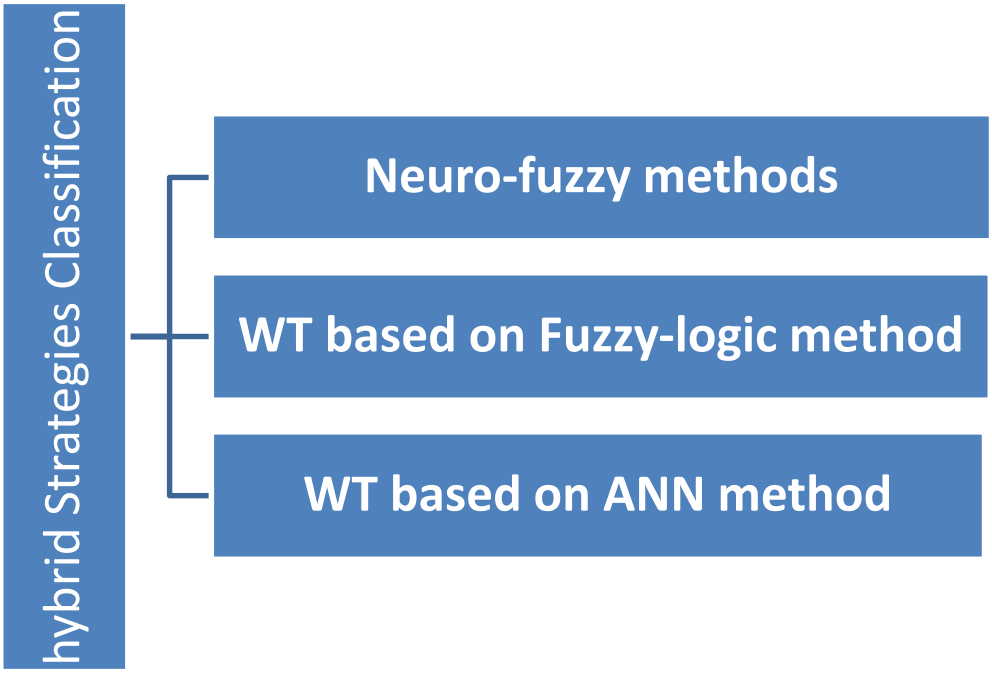


Fig. 2.4. hybrid Strategies Classification

a. Neuro-fuzzy methods

Combining NN with (FL) allows learning from the historically obtained sets of data. The technical points on classifying shunt faults using neuro-fuzzy method was explained in [80]. As input to the neuro-fuzzy system, a symmetrical component, pre-fault and post-fault currents that refer to 3 phases have been used.

b. WT based on Fuzzy-logic method

In References [79,81] Fuzzy-logic based WT to classify various forms of shunt faults. For the classification and detection of power system, Reference [78] also used hybrid of WT and FL methodology.

c. WT built on ANN method

To obtain the distinct features, an established method in [12] was based onto DWT. Such features then were supplied into Probability Neural Network (PNN) for purposes of classifying faults. In [82] a new technique for the idea of fault classification was performed using hyperbolic s-transform, based on the neural-network radial-based function (RBFNN). A novel approach for categorizing shunt-fault types was also produced in [44] that used integrated multi-wavelet packet entropy method with RBFNN. The approach in [77] by integrating DWT with ANN methodology identified the fault forms through voltage and current readings.

IV. Logic flow method

In case of classification of faults structures does n’t depend on Smart / Artificial Intelligence for applications or implementations, a flowchart based logic flow on many parameters is typically used without using any classifier technique. The strategies for classifying fault could be divided as shown by various network structures. Two groups are involved: two-terminal and three-terminal strategies.

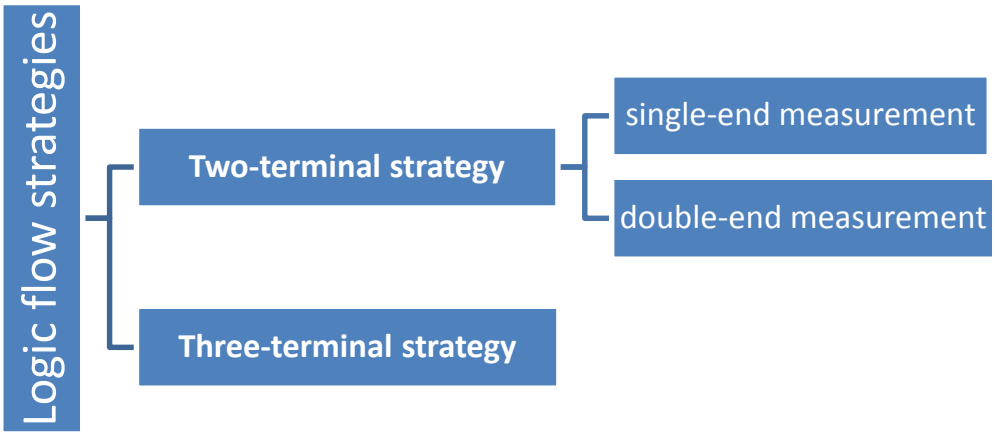


Fig. 2.5. Logic flow strategies Classification

a. Two-terminal strategy

There are two main types from the perspectives of measurement availability for fault classification in power grids: single-end measurement and double-end measurement systems.

Numerous techniques, obtained from single end measurement system, provide a higher velocity and lower effect on outside phenomenon such as noise [33, 40, 56, 77, 83, and 84]. Techniques that used a single end measurement method will be significantly impacted by the resistance of fault. The effect for fault resistance upon its accuracy of its particular distance and the necessity of the equivalent of thevenin is the biggest issue with regard to such techniques.

Double-end measurement system methods are attributed to the higher reliability in order to differentiate between the various types of faults although they require formal communication system that sends as well as synchronize the measurement results across two terminal ends [85, 86]. Such approaches were based on Sync of Measurement (voltage and currents), which were obtained as a communication network by the GPS. At reference [86], synchronized two-terminal measurement were established, as well as the recorded voltage and current waveforms were used for classification of faults.

The three-terminal system attracts significant attention over the two-terminal system due to economic, technical and environmental validity. Protecting three terminal circuit design, besides this, isn't as easy also as two-terminal method.

b. Three-terminal strategy

Protection of Three-Terminal strategy requires classification of faults and the identification of faulty phase. Such processes are important to limit its time abrupt and accelerate the restoration of electric utility. Those who are also used to verify the strategies for single-phase tripping as well as the mechanism for auto-reclosure [52]. Resulting in significant conditions, the method of fault detection through three terminal circuits seems to have more difficulty. Nevertheless, the consistent and reliable fault identification system is developed to mitigate the effect of faults on teed circuit reliability [87]. The detection of faults and the choice of faulty phases have many important features in studies of fault recognition on three terminal circuits.

2.3 Determination of fault location (in case of faulty signal only)

Single phase tripping, line to ground faults and auto-reclosure were widely used in long-line processes containing tripping the faulty phase. Classical phase selectors may endure certain areas of weakness owing to various operating systems and abnormal situations. Furthermore, an invention of wavelet transformation methods and the capability to concentrate on transients offers an efficient and consistent tool for precise and quick identification of phases. Even so, at reference [45], just the type including its fault (if LLG or LG) was defined as well as the trust component, although there was no specific determination of the faulted phase. In reference [88] the researcher introduced an innovative idea relying ANN and approach with in detection of faulty phases in smart grids. In reference [89], the faulty phase classification is done utilizing sharp transitions produced upon this faulty phase relying on WT. In reference [90], the researcher proposed a new faulty phases selection method dependent upon traveling wave as well as wavelet transformation.

CHAPTER 3

CHAPTER 3

DATA FUSION TECHNIQUES

3.1 Introduction

The fusion of data as a particular study field can date back to the 1990s [91, 92]. Data fusion was also described as the production of datasets from various outlets. This chapter investigates the state of field of data fusion, and discusses a really related survey. Also in initial stage, we explain as well as discuss various categorization trends for data fusion. Utilizing data/information fusion strategies, all operations requiring some kind of variable calculation from various sources may usually be improved.

Usually, the terms "information fusion" and data fusion "can be used as substitute to each other; however, the term data fusion is being used in places for data sources and the expression" information fusion "is being used to denote fabricated data. In short, we may describe data fusion as a mixture of different resources in order to get good information. Techniques of data fusion have traditionally been used in multi-sensor systems also with purpose of combining and mixing sensor readings. The aim of data fusion that are used in multi-sensor areas may be to obtain good efficiency and decreases chances of occurring error that use many centralized data sets.

Such-as fundamental component of manufacturing, sensors from different types are installed and fitted in various systems [93, 94], perfectly fulfilling the requirement for data collection [95, 96] and detection of faults [97-99]. So many difficulties occur while fusing data is added into the system, which include risks and uncertainties about data and information strategic planning.

And important approach for dealing with the large data is the extraction of features [100-102]. Numerous strategies have been widely discussed for the diagnosis of faults with the combination of fusion techniques. In fact, the authors in reference [103] merged various techniques for various uses in order to detect faults. As well as the ANN, WT and the decision tree have been used to recognize the faulty condition. The algorithm in [104] uses fast Fourier transform as a feature extraction technique to validate several output metrics and perform signal tracking using ANN, SVM and k nearest neighbor classification methods. Lately, an advanced multi-sensor data fusion approach is involved with the aid of a relevant vector machine for the identification of faults in gearboxes, and an ant colony modeling system [105]. The suggested compound approaches, though, are comprised of different methods, which can result in the difficulty of the analytical process for identification of faults. Towards the aim of consistent results for detecting data preprocessing, there could also be several other brief techniques or just one technique to monitor and detect the entire system [106-109]. In addition, the data fusion approach was used as a pre-processing tool for getting higher-order composite spectra, during which the main component technique was used to detect faults [110]. Almost all of the fusion techniques demonstrate their success in local applications, while in realistic real-world environments, where sensor-generated data could be enormous, and these methods could miss the benefits of system also might incorrect results were obtained. The system is typically challenged with wide scale as well as complex logic in so many various areas, In addition to a maximum variance of sensor-collected data. Under these conditions, many multiple learning algorithms attempting to minimize dimensionality reveals its benefit in data mining [111,112]. The thesis contains numerous definitions for the term " data fusion, "that differ primarily in based on the extent of generalization also and due to different fields of the studies. The Joint

Directors of the Laboratory (JDL) and the US Department of Defense (DOD) proposed the most common definitions, at least with in multi-sensory field [113], In which DF is described as: *"A process dealing with the association, correlation, and combination of data and information from single and multiple sources to achieve refined position and identity estimates, and complete and timely assessments of situations and threats as well as their significance."*. To conclude, similar to the various concepts and disciplines is the idea that DF is a structure, designed with a collection of instruments, for the collective processing of data via various sources that enables information/knowledge not to be retrieved with individuals, while the level of generalization of the technique is distinctive. Apart from the DF concept, the so-called thresholds at which "fusion" is being performed are another taxonomic issue. Three types of DF have been defined [24] and are now a basic classification, for example in chemo-metrics and related fields of application [114-116], specifically, low level where DF techniques are applied immediately to source data; Mid-level in which DF acts on features extracted from each established of information; and high level that decision (design resulting) is fused from the processing within each block of data.

3.2 Data-fusion classification approaches

Data fusion is indeed a combination of many scholarly different disciplines involving multiple areas, and founding a perfect and intense classification becomes very complicated. The approaches and procedures used can be listed as follows:

- Assisting with input / output data types and nature [117].
- Based on the relation between the sources of inputs [118].
- Established on type of architecture

- Derived from various degrees of data fusion discussed through JDL

3.2.1 Assisting with input / output data types and nature

Dasarathy [117] given are the most well-known data fusion schemes and includes a set of 5 modes as below:

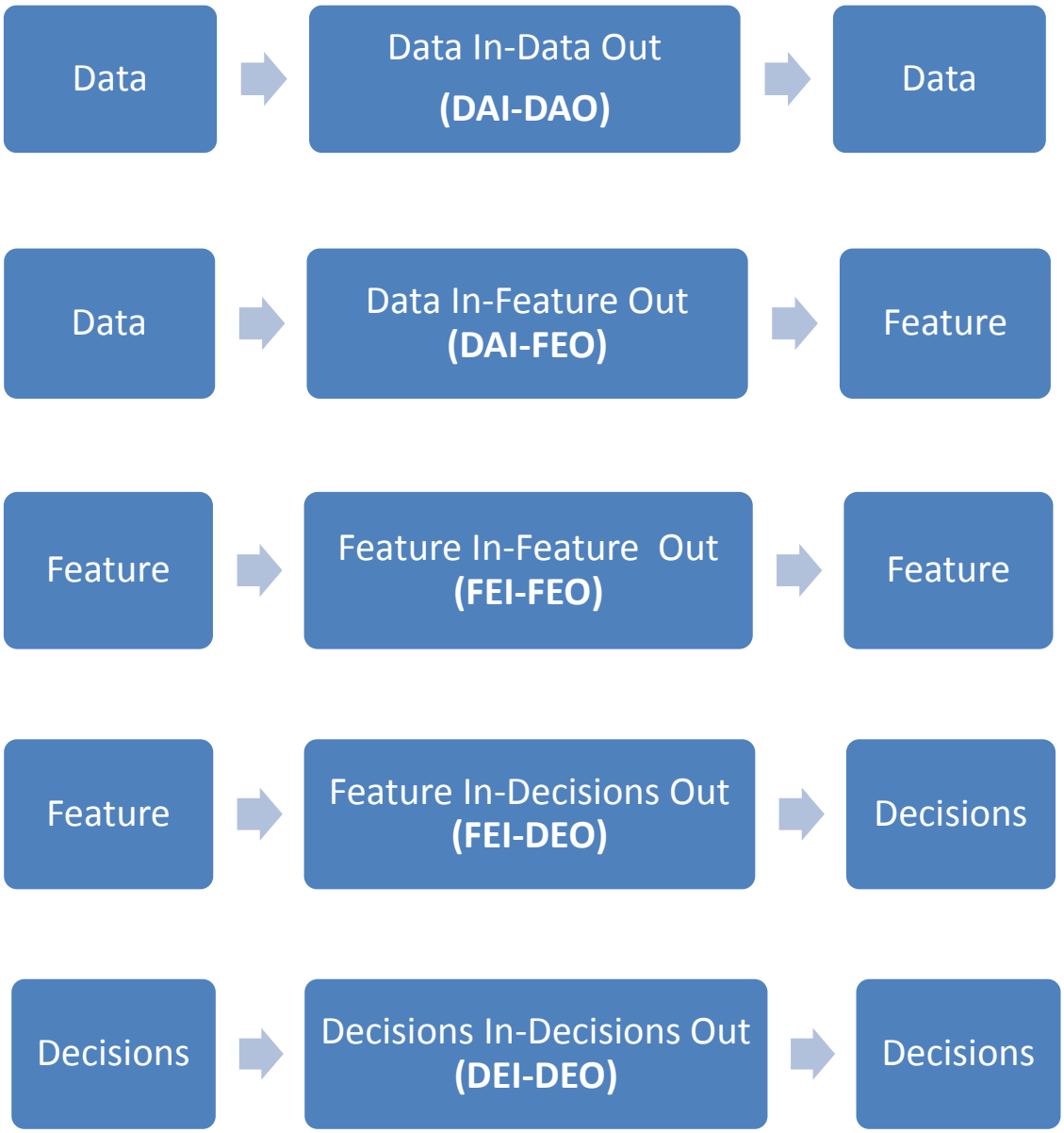


Fig. 3.1. input / output data types and their natures.

I. Data In-Data Out (DAI-DAO):

That hierarchy is the most basic or simplest type of fusion imaginable. This fusion process is widely known as a data fusion, being that of fusion of data inputs actually results in a type of data output. The results are classically more consistent or reliable. Some of the processing methods used in multispectral data analytics systems that are remote sensing techniques drop under this classification.

II. Data In-Feature Out (DAI-FEO):

This could be the next step taken within that ladder of five levels. It incorporates data from various sensors to extract a type of an object behavior in the system or a phenomena description being observed. Based on someone's viewpoint, input-fusion of information or output-fusion results in a feature, fusion in this form was known either as a feature fusion or a fusion of data. Feature fusion was called as three names such (information, intermediate level, symbolic) fusion, etc. One such fusion type could also be the initial step in some situations, only with prior type completely missing.

III. Feature In-Feature Out (FEI-FEO):

Consequently, feature fusion is another name to this type of fusion. Within that point of a structure, all input and output were also features for fusion method. A data fusion technique therefore identifies a number of features in which to enhance, modify or gather innovative features. A further research which has some significant opportunities on that feature level fusion was presented as super feature [119]. The methodology to super features might synergistically fuse features through distinct sensors into a series of super feature. In any mathematical context, such super feature describe the differences in the actual feature value compared to each other. A dimensionality of a

resulting feature vector may either depend on or be independently of a dimensionality of single sensor feature vector, depending on the particular super feature utilized. This flexibility can be important in reducing computing demands for issues with different features each involving a wide range of sensors.

IV. Feature In-Decision Out (FEI-DEO):

This type may be the most growing concepts of fusion techniques. Now this inputs are perhaps features of specific sensors, as well as its output of a fusion method is a decision like the identification of target class. Yet again this process was already classified to as either feature fusion or decision fusion, based on researcher's viewpoint. Many information processing mechanisms connecting inputs from various sensor have been operating for a long time, in which a decision is listed in the feature vector derived from the previous information and/or practice.

V. Decision In-Decision Out (DEI-DEO):

Decision fusion is another name for this kind of classification. All outputs and inputs also seem to be decisions herein, and maybe this style reflects a really learned fusion pattern [120,121]. The input decisions are fused to achieve improved or novel decisions.

3.2.2 Based on the relation between the sources of inputs

Durrant-Whyte and Hugh F. identified three categories established on the relations between the sources [118] as shown in next figure:

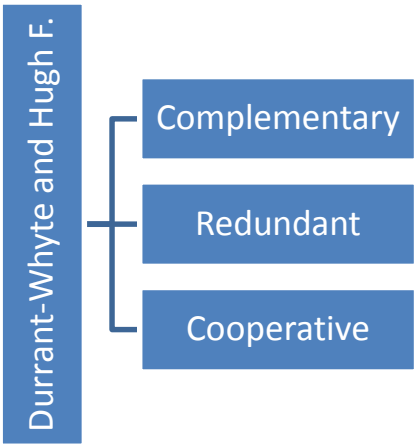


Fig. 3.2. Durrant-Whyte and Hugh F. categorization

I. Complementary:

Where the i/p source data shows various areas of an environment and may therefore be used to acquire extra detailed comprehensive data. As the input sources information denotes different portions of the scene and used to achieve more wide-ranging information. e.g., Data obtained from two cameras of various cross sections on a certain objective could be classified as complementary.

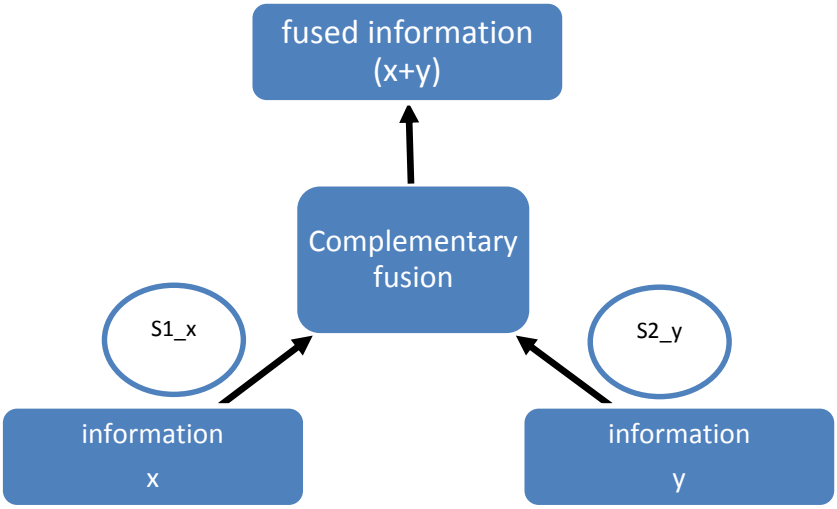


Fig. 3.3. Complementary fusion schematic

II. Redundant:

If multiple i/p sources offer relevant data on a target and can therefore be combined to improve results. For e.g., information from interfere regions in sensory networks is assumed redundant.

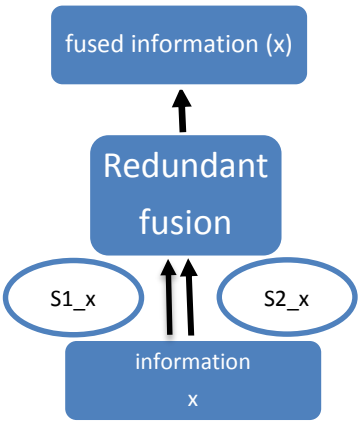


Fig. 3.4. Redundant fusion schematic

III. Cooperative:

Once the data supplied is merged to new data which is usually more complicated than that of the data initially given. For e.g., Multi-modal fusion of data (video and audio) is known to be cooperative.

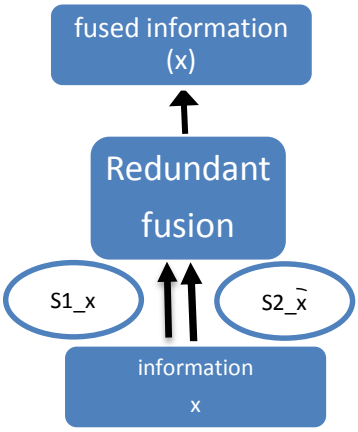


Fig. 3.5. Cooperative fusion schematic

3.2.3 Established on type of architecture

One of the major issues which appear whenever creating a data fusion process is where the process of data fusion is also executed. The below three styles of architectures may be defined on the basis for such criterion:

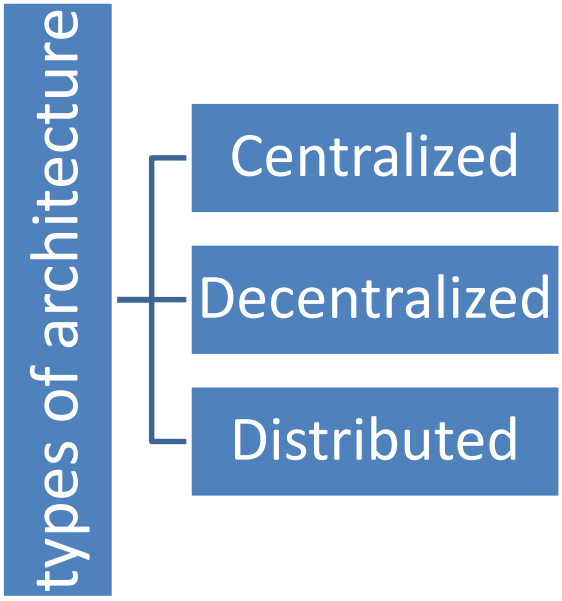


Fig. 3.6. styles of architectures

I. Centralized:

A fusion unit remains in central processor collecting and analyzing data from any and all sources of data. So, overall fusion operations are carried out in a central processor which utilizes their raw measurement from the sensors. Under this system, only the observations data were measured by the sources will be sent to a central processor, in which data fusion strategy is carried out. The centralized architecture is practically ideal if users believe the data association and data alignment are done properly and as such the time taken to send the data isn't really important. Typically, though, the preceding hypothesis isn’t suitable for actual situations. In fact, another

drawback for the centralized architecture is the vast amount of capacity that is needed to transmit raw data at the same time. Ultimately, the delay time in transmitting data between various sources are dynamic and influence the result of the centralized system.

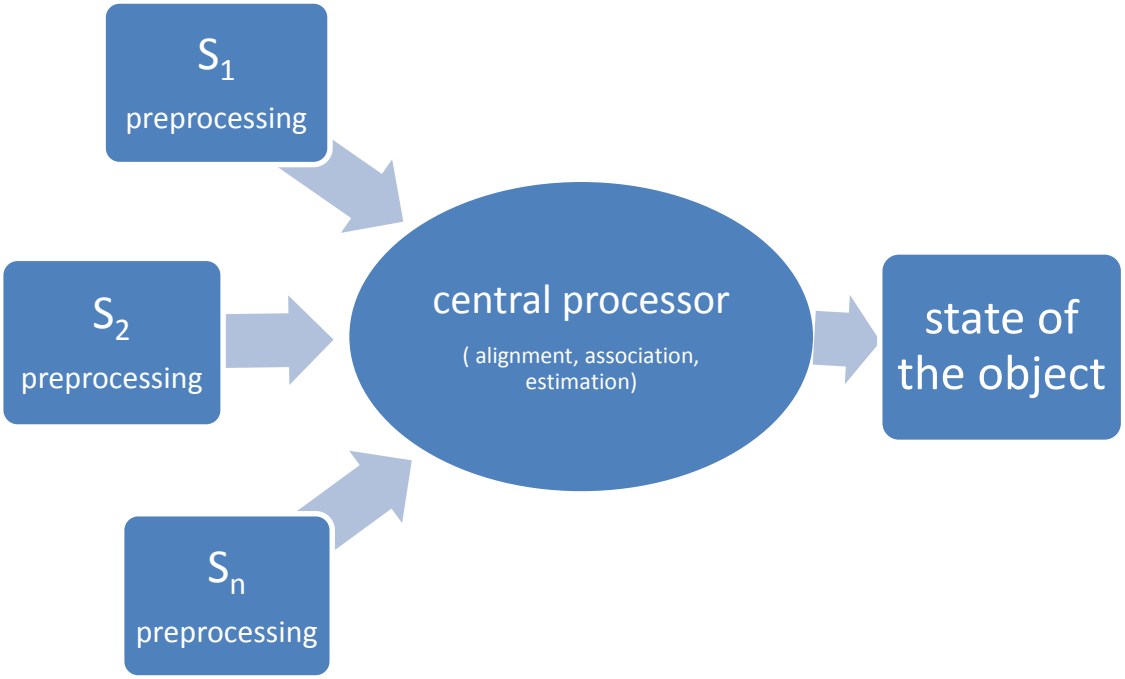


Fig. 3.7. centralized architecture.

II. Decentralized:

This type of architecture consists of a set of nodes, where every node has its own computing ability so no individual data fusion position occurs. Consequently, every node combines its own resources with data received from its peer groups. Data fusion is executed independently, for every node responsible for their native data and their peer's data obtained. the Fisher and Shannon measurements are usually utilized in Decentralized data fusion methods to connect data

instead of the object state [122]; Thereby, if the sensor nodes is raised, that kind of architecture can endure from scalability issues; The full data fusion mechanism is carried out from each node throughout the decentralized approach, so that each node produces a global merged output.

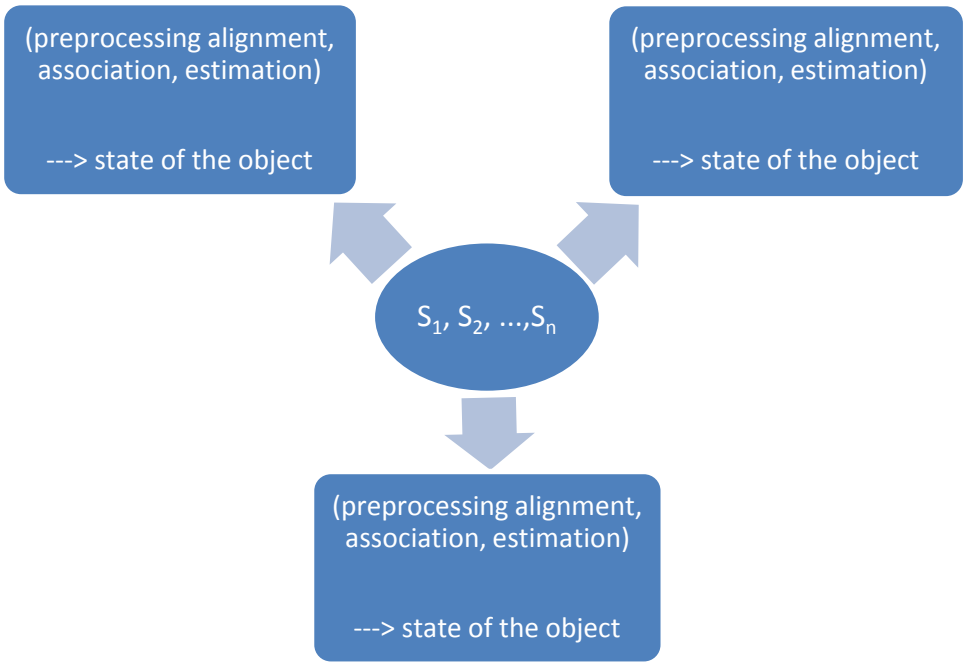


Fig. 3.8. decentralized architecture.

III. Distributed:

At this scheme, readings were also executed independently for every node prior the data is transmitted to their fusion node which collects the data from other nodes. Within these statements, the estimation of the state and the association of data are carried out in source node prior the data are shared to its fusion node. Hence, also every node gives an approximation of the object state relying on its

native opinion, but this data seems to be the inputs to the fusion node, that offers a fused broad perspective. That architectural style proposes multiple choices including variations which ranging just from single fused node towards multiple distinct fusion nodes. Pre-processing of the collected measures is done in the distributed architecture, resulting a feature vector. Distributed techniques generally show a similar view of state (situation, speed, and similarity) including the related likelihood used to meet those requirements of fusion [123].

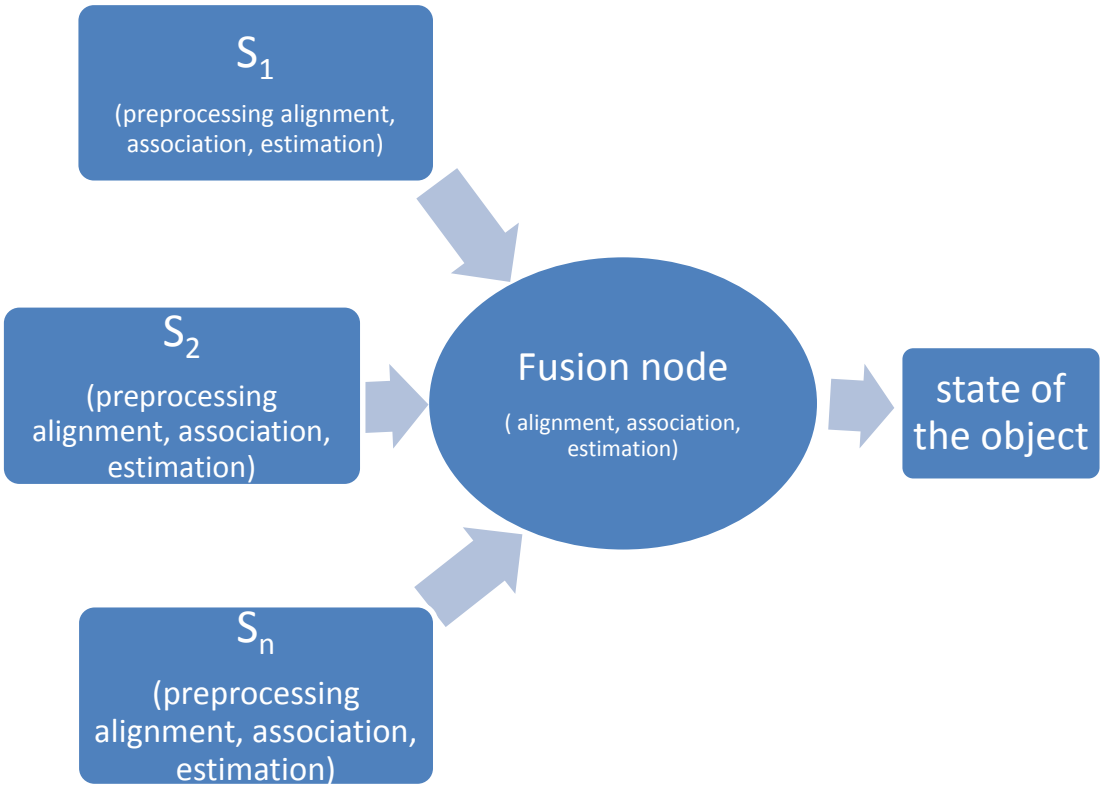


Fig. 3.9. Distributed architecture.

In theory, the computing and connectivity criteria make it increasingly challenging to utilize a decentralized data fusion method.

To fact, though, that's no one perfect structure. As well as the extreme suitable architecture are being selected according to demands, requirement, current systems, information obtainability, and categorization data fusion scheme.

3.2.4 Derived from various degrees of data fusion discussed through JDL

This class seems to be the most common theoretical structure within that field of data fusion. Initially suggested by JDL and DOD [124]. Those organizations categorized a data fusion system to 5 scales of handling, a database associated, and a data bus connecting the five elements. The five stages may be divided into two main categories, low-level and high-level fusion, which include the next contents:

I. Source:

These sources shall be responsible for supplying their data input. Various kinds of data sources, like sensor devices, a priori data, documents, and humanity input can be utilized;

II. Human computer interaction (HCI):

It is a module which enables inputs into the process from operator and delivers operator output. It contains questions, instructions as well as the results gained.

III. database managing scheme:

At this type, delivered data and fused results are stored. This system is a serious component due to the huge amount of highly different information that are stored. Because of the vast volume of

extremely complex information that is processed, makes this device is a vital element.

Conversely, the 5 data processing categories are set as:

I. First stage:

Source preprocessing stage is lower than others for the system of data fusion, as well as it comprises the lower fusion stage such as signal and pixel stages. Throughout the situation of text sources, that stage often involves the method of extracting information. Such stage decreases data storage capacity and preserves valuable data to higher levels mechanisms.

II. Second stage:

Object refinement utilizes produced data of prior stage. Routine methods during that stage involve association, spatial-temporal alignment, and correlation, grouping or combining methodologies, system identification, reduction of false positives, fusion, as well as combination of processes extracted. Such a stage's achievement outcomes are discriminate for objects (identifying and classifying), as well as track for objects (orienting and objects state). This step converts any i/p information to regular structure.

III. Third stage:

Situation assessment stage is intended at a high illation level than second stage. This helps to classify the possible scenarios and the evidence gathered. Situation assessment sets up relations between object classes. Relations are respected to evaluate the nature of object in a particular situation. The objective in that stage helps to perform high-stage illation and highlighting critical activity (through particular, patterns). The result is a collection of illation of high level.

IV. Forth stage:

Impact assessment analyzes the effect of identified third stage events with a view to obtaining a good vision. The present scenario is analyzed, and a prospective forecast is carried out to determine necessary dangers, weaknesses, and chances for activities. It contains two major points, first, a probability or hazard estimation, and second, a forecast of logic results.

V. Fifth stage:

Process refinement is the final level which enhances the operations from first stage up to forth stage and creates a management of the resources and sensors. The objective is to deliver effective managing of resources whilst also taking account for strategic goals, organization and management appropriate resources.

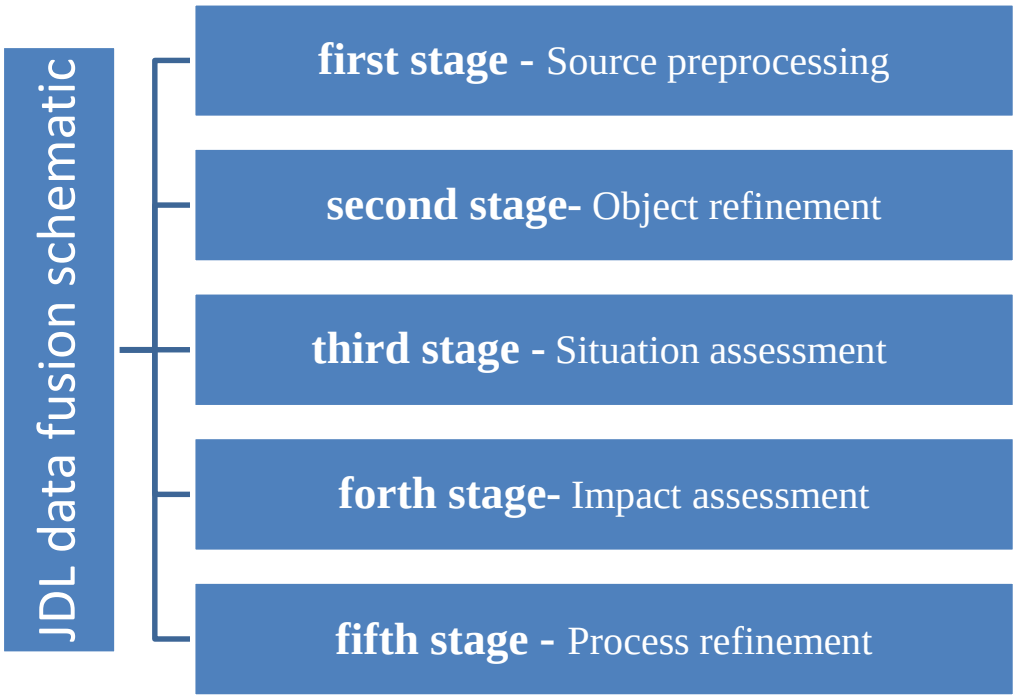


Fig. 3.10. the JDL data fusion schematic.

CHAPTER 4

CHAPTER 4

SIMULATION STUDIES AND RESULTS

4.1 Introduction

The new proposed technique and DWT are applied to the IEEE standard 14 bus system as shown in figure 4.1 to detect the fault index time and its location. This system is used as one of the main power systems, this power system is widely used as a study case for its sensible complexity and structural matching compared to micro grids [125]. To test the reliability and consistency of the proposed model, several faults are introduced into the system at different bus locations.

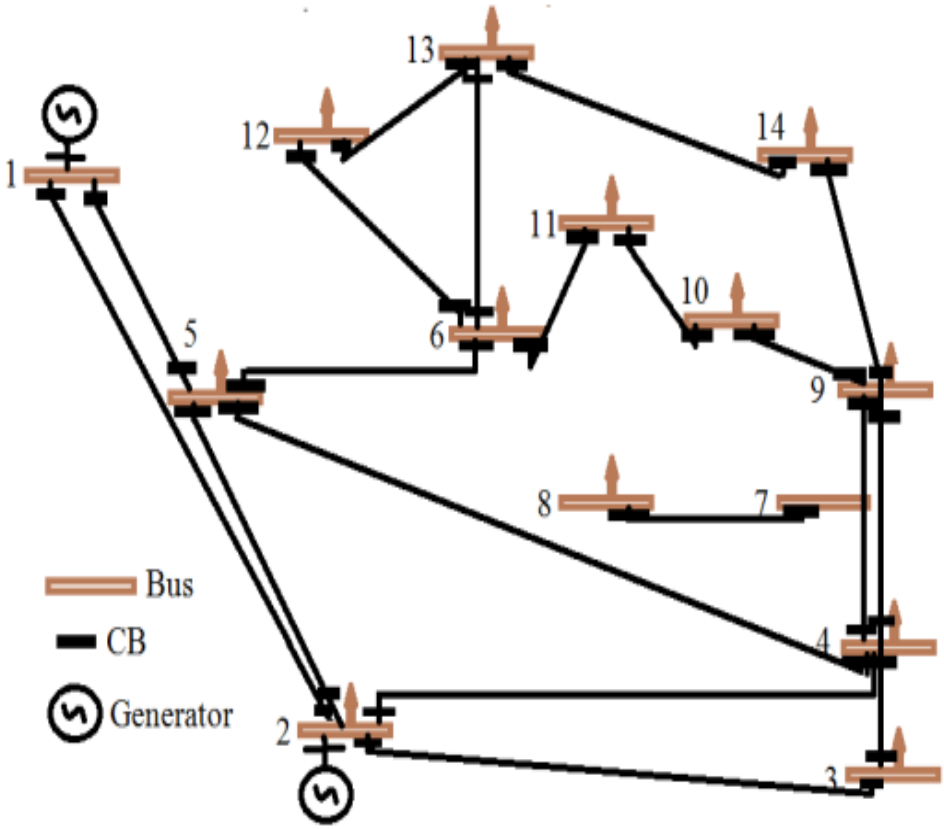


Fig. 4.1. IEEE standard 14 bus system [11].

A simplified flow chart of proposed method is shown in Figure 4.2. First, the weight of the incoming signal is calculated, and then the learner classifier determines that if this signal is faulty or not. the proposed 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 of complex tree classifier that rehearses more signals and the model is prepared when any obscure signal can be classified as noisy or faulty emphasis on the estimation of signal weight as a summation of square sample values for all signals. For the same duration, this will impact the weight of 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 used 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, All 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 decision of the complex tree learner classifier [11].

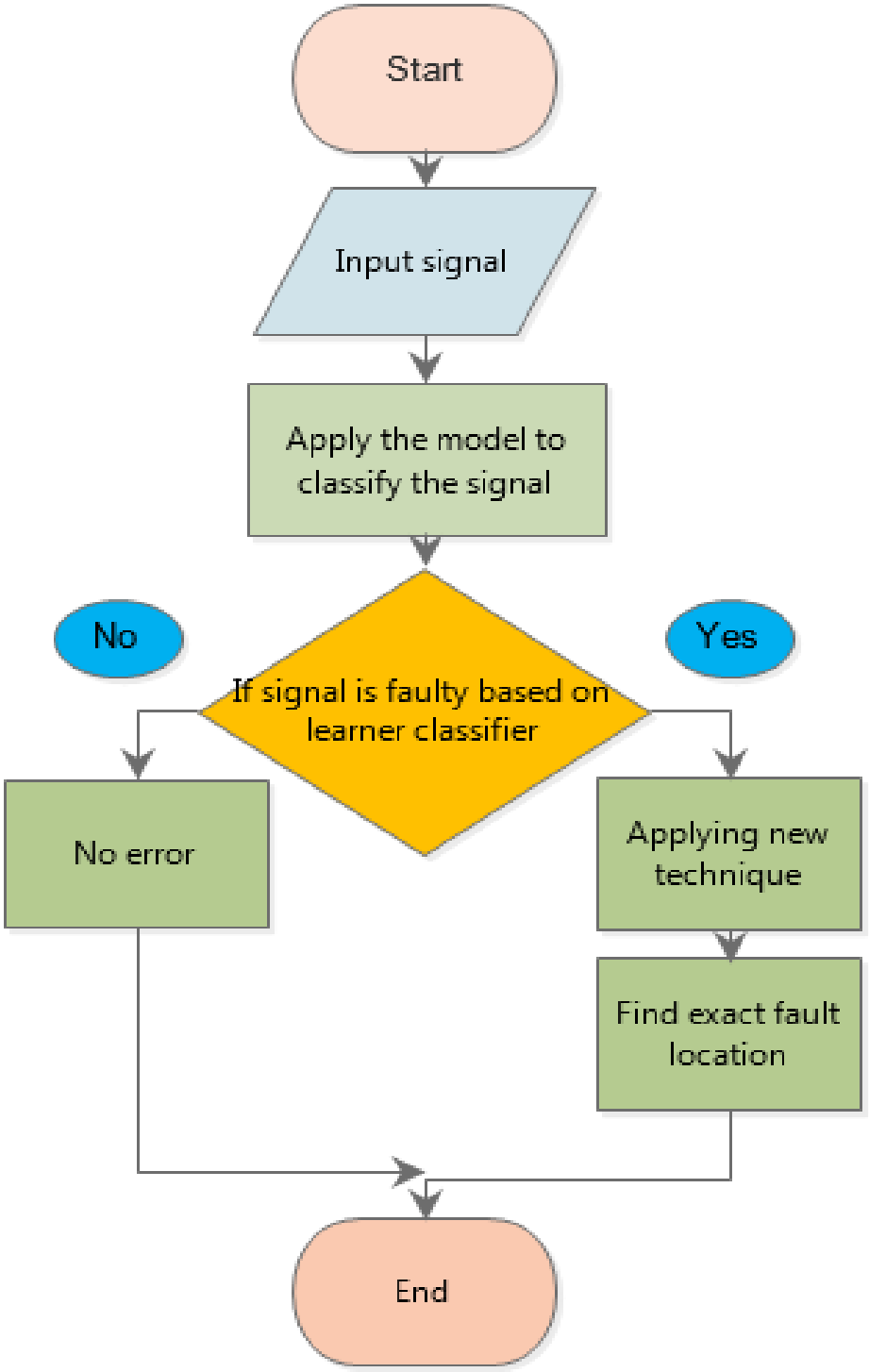


Fig. 4.2. The flow chart of proposed method [11].

4.2 Simulation of faults scenarios

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

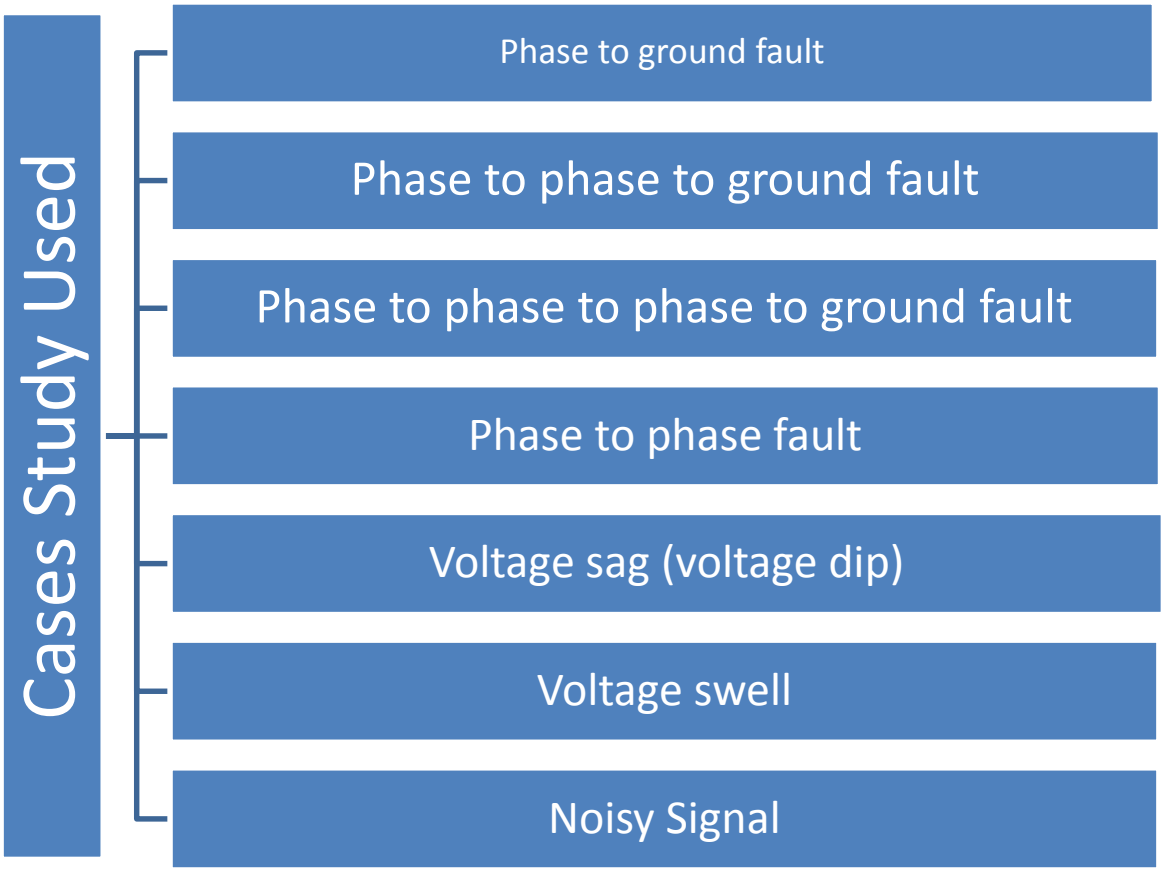


Fig. 4.3. Cases Study Used.

4.2.1 Phase to ground fault

A brief short circuit between line and ground, exceptionally regularly caused by physical contact, for illustration due to lightning or other storm harm. Figure 4.4 (c) 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. The following four figures (4.4 - 4.7) appear all 14-bus signals with their DWT exclusively for each signal.

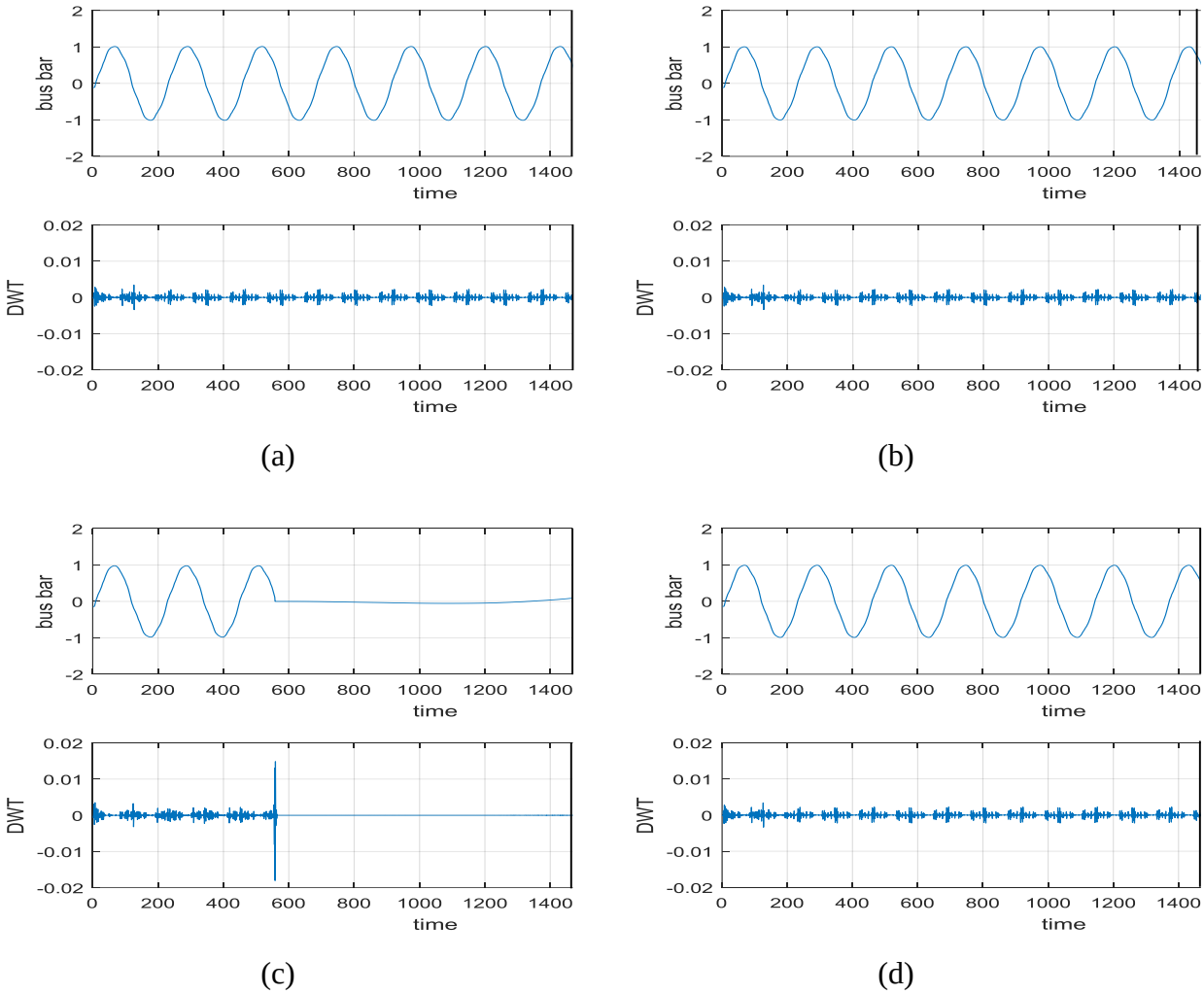


Fig. 4.4. Bus signal and its DWT for (a) bus1, (b) bus2, (c) bus3, and (d) bus4.

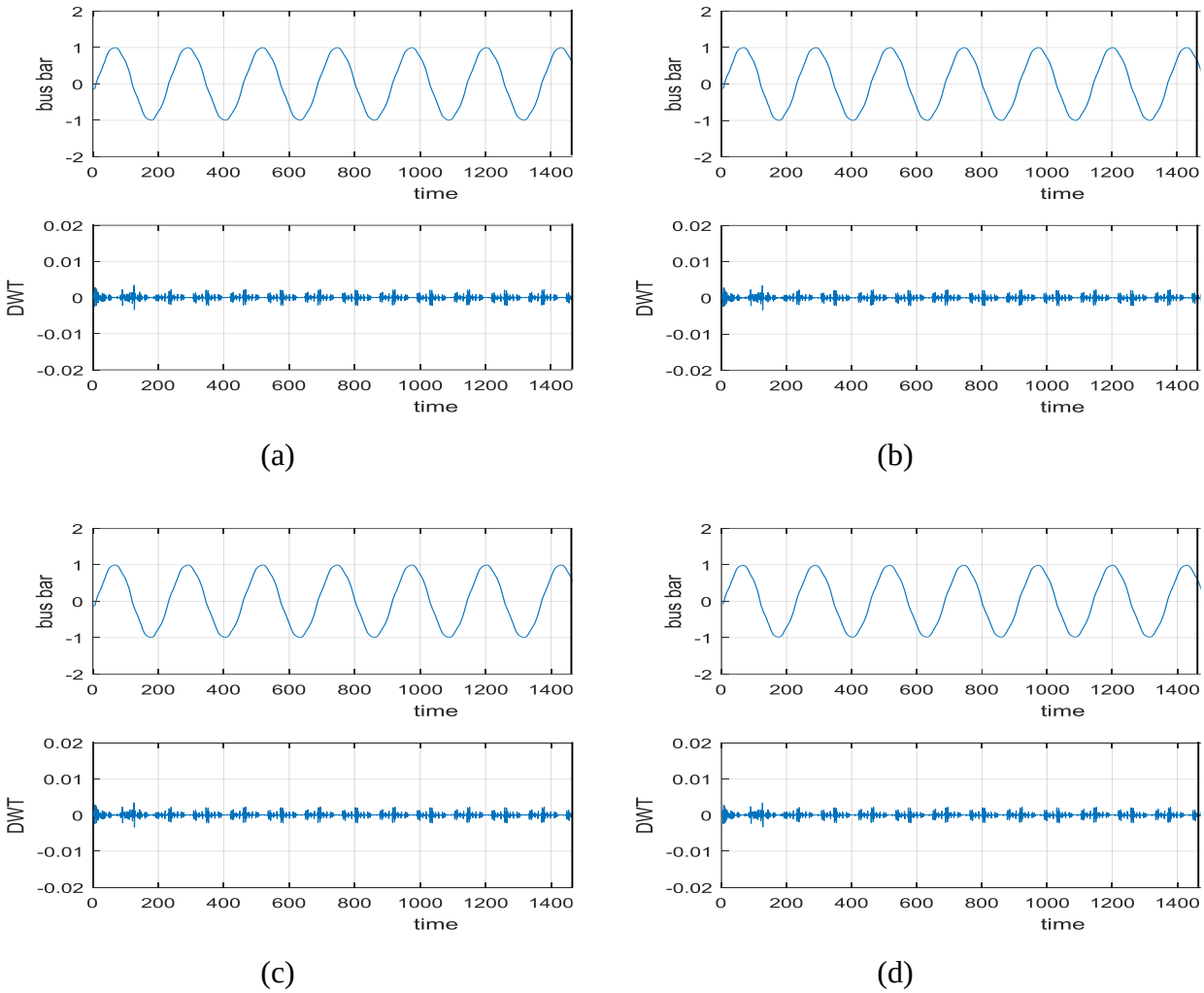


Fig. 4.5. Bus signal and its DWT for (a) bus5, (b) bus6, (c) bus7, and (d) bus8.

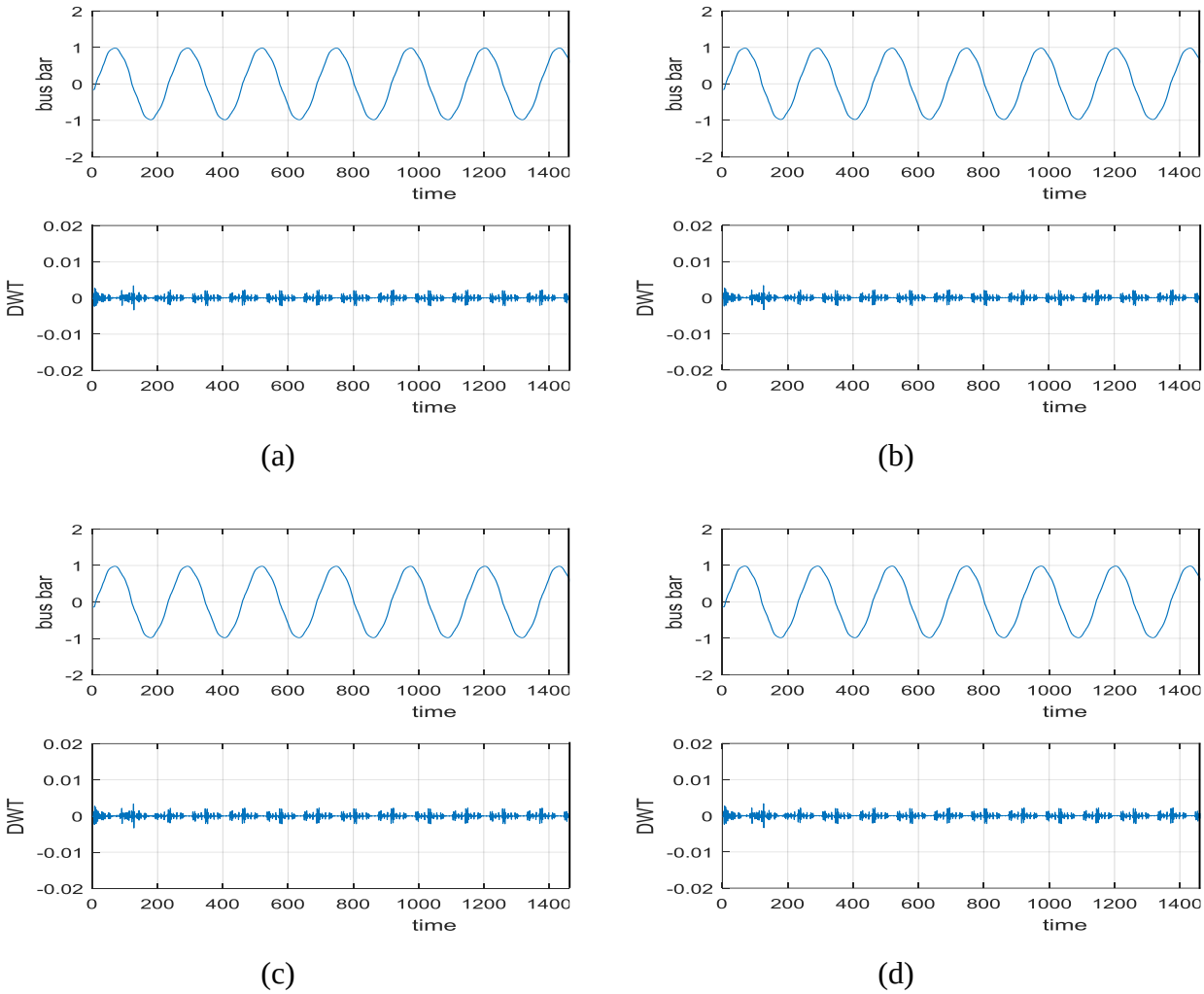
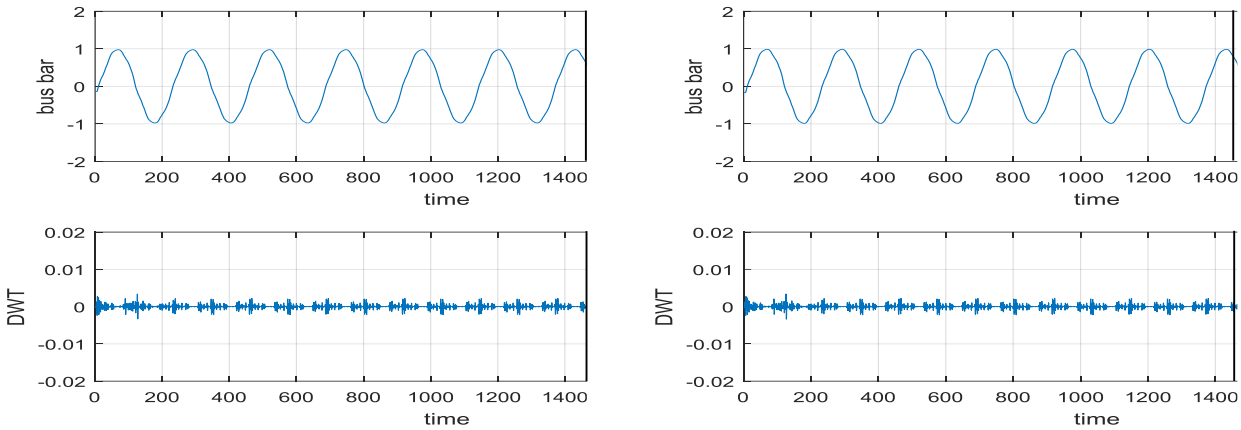


Fig. 4.6. Bus signal and its DWT for (a) bus9, (b) bus10, (c) bus11, and (d) bus12.



(a) (b)

Fig. 4.7. Bus signal and its DWT for (a) bus13, and (b) bus14.

Fig. 4.4(d) shows the defective signal of bus 4 and its 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 method or by using the proposed technique produced in this thesis.

Fig. 4.8 displays the output of the suggested faulty signal, DWT and new technique. As shown in this figure, the DWT technique identifies the defective signal at bus 3 at the sample index of 559 where the 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.

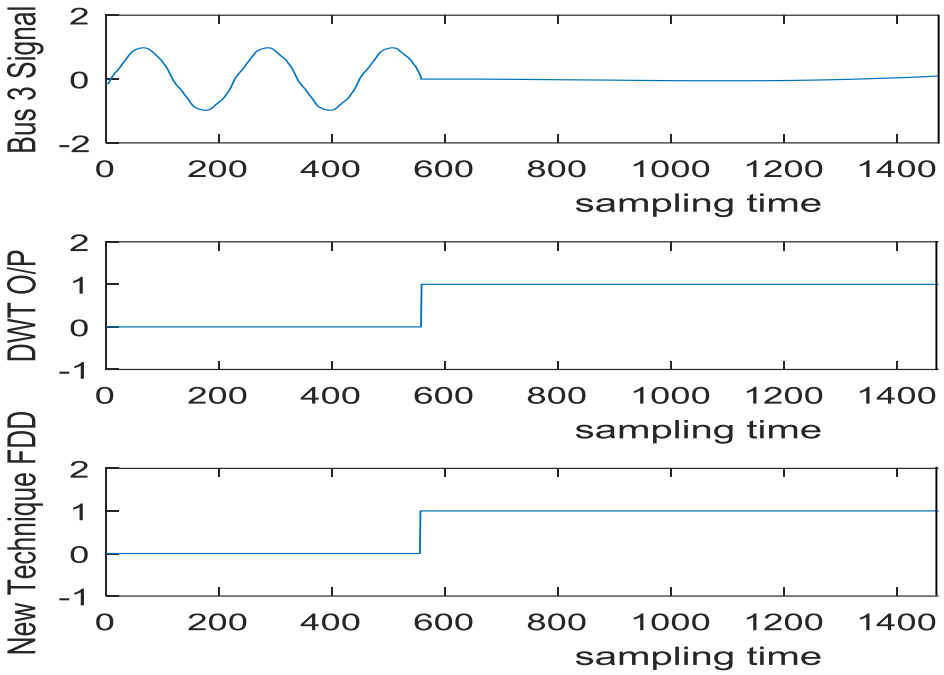


Fig. 4.8. Output of faulty bus signal, DWT, and new technique FDD system.

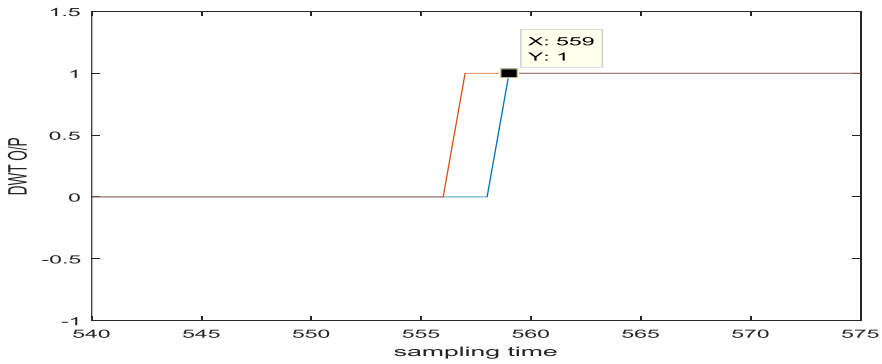


Fig. 4.8. Exact reading of DWT technique.

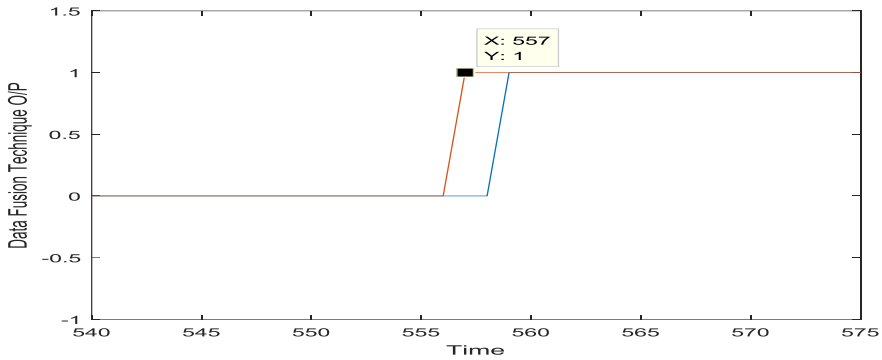


Fig. 4.10. Exact reading of new data fusion technique.

4.2.2 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.

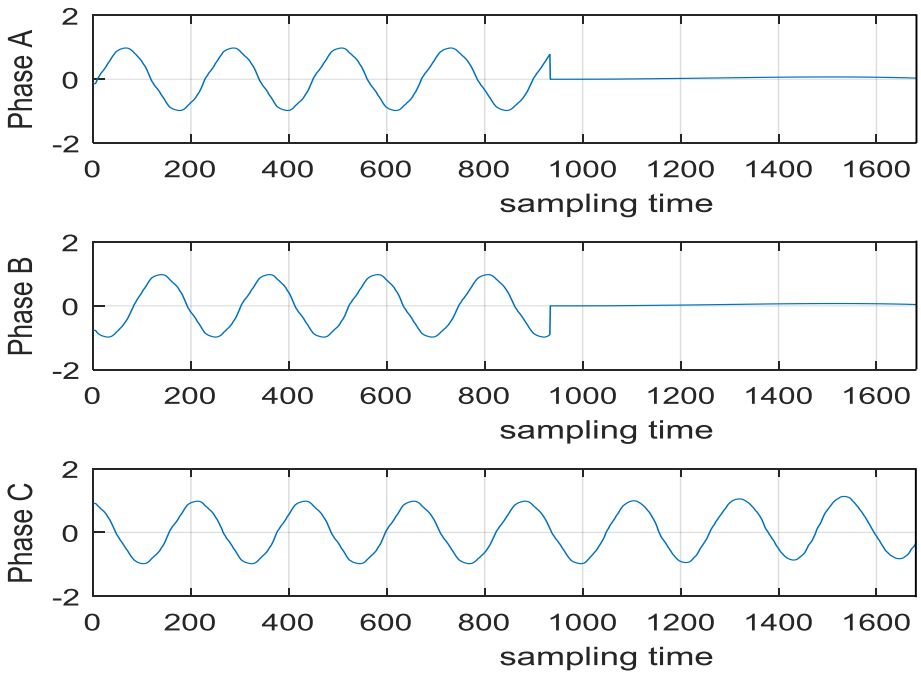
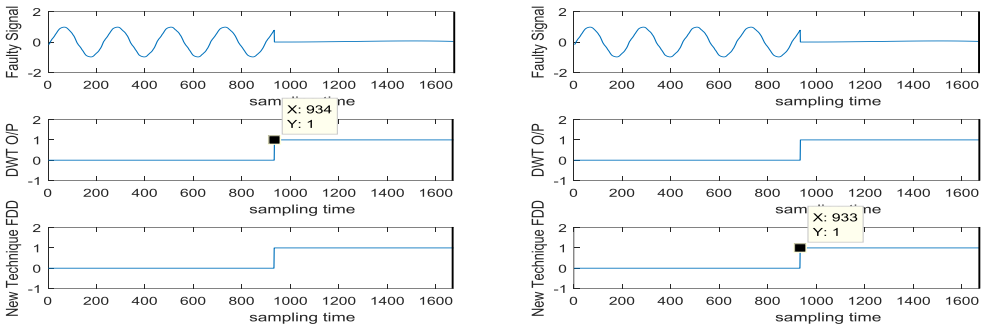


Fig. 4.11. Phase to phase to ground fault signals.

The DWT output for this signal clears that the CD_1 value for bus 3 shifts from nearly nil to 0.127895860718947 Pu at 934 sampling time, while in bus 4 the corresponding value increases as the highest value to 0.003574276727847 Pu.

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.



(a) DWT fault location (b) new technique fault location

Fig. 4.12. Output of new technique FDD system for phase to phase to ground fault.

4.2.3 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. The fault occurred at sample index 953 as shown in the next figure.

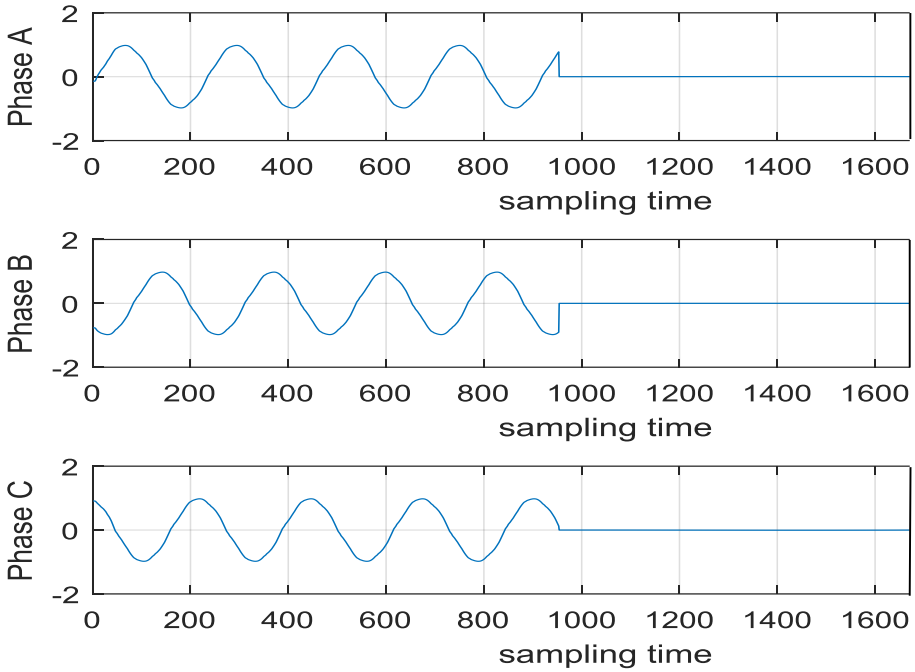


Fig. 4.13. Phase to phase to phase to ground fault signals.

The DWT output for this signal clears that the CD_1 value for bus 3 shifts from nearly nil to 0.127892004625002 Pu at 954 sampling time, while in bus 4 the corresponding value increases as the highest value to 0.003486327605171 Pu.

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 953 and 954 for proposed data fusion technique and DWT respectively as shown in next figure.

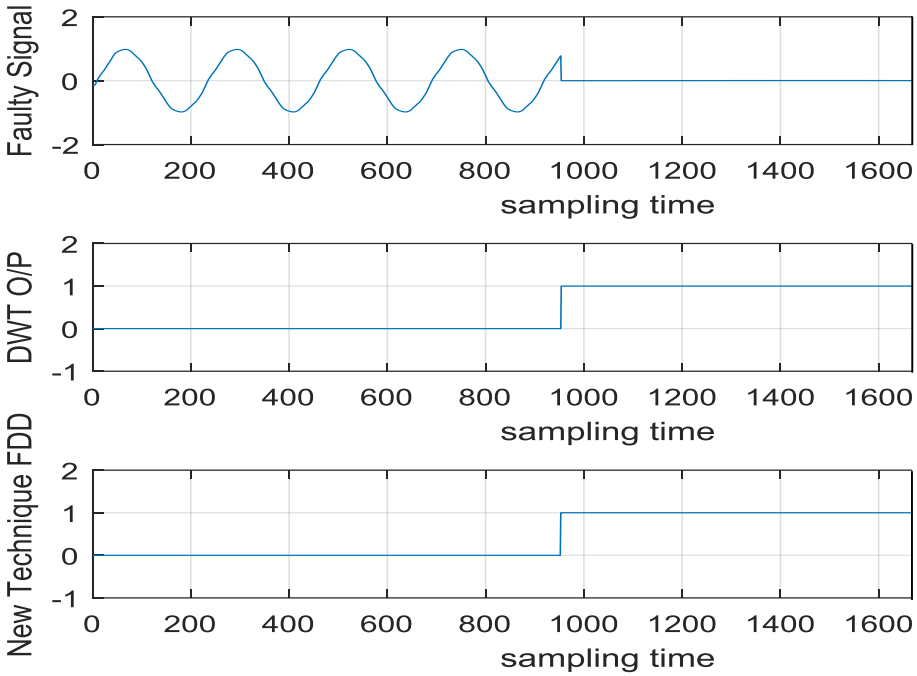


Fig. 4.14. Output of new technique FDD system for Phase to phase to phase to ground fault.

4.2.4 Phase to phase fault

Line-to-line-a short circuit between lines caused by air ionization or when lines are in physical contact, e.g. due to a cracked insulator where fault occurred at sample index 953 as shown in the next figure.

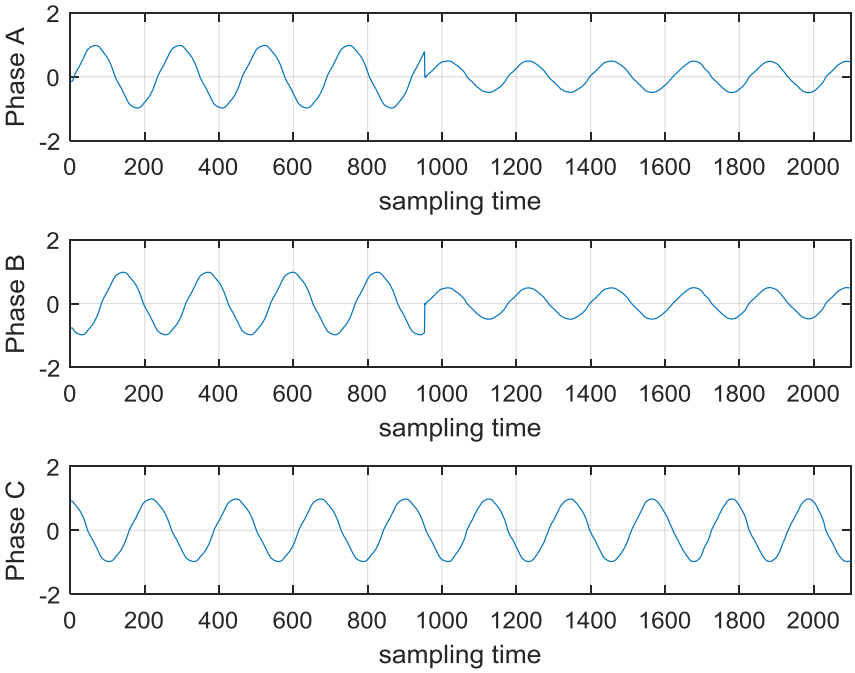


Fig. 4.15. Phase to phase fault signals.

The DWT output for this signal clears that the CD_1 value for bus 3 shifts from nearly nil to 0.128556478268647 Pu at 954 sampling time, while in bus 4 the corresponding value increases as the highest value to 0.002537475124146 Pu.

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 precisely with sampling time 953 and 954 for proposed data fusion technique and DWT respectively as shown in next figure.

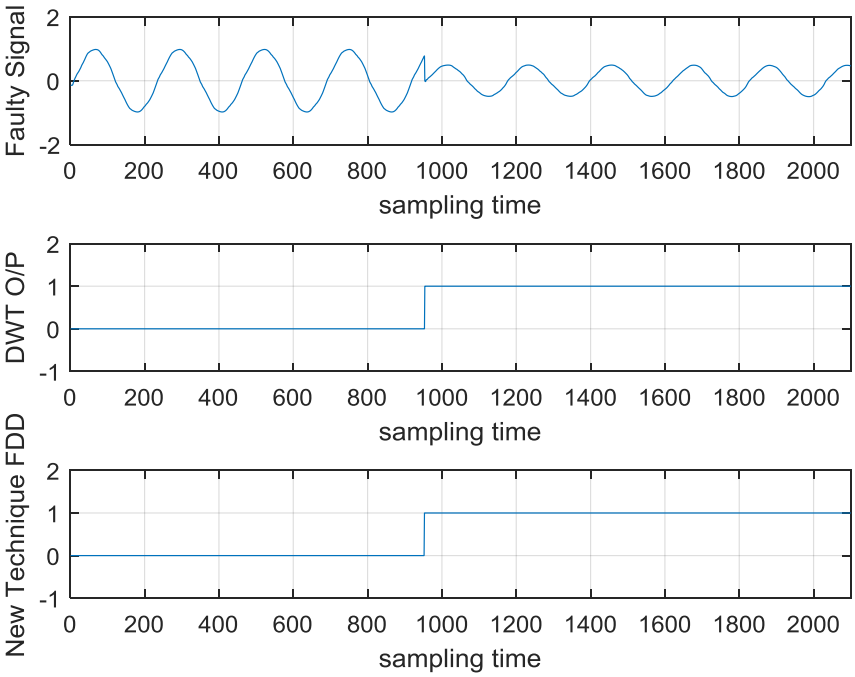


Fig. 4.16. Output of new technique FDD system for Phase to phase fault.

4.2.5 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 as shown in figure 4.17. The used case utilized starting fault location occurred at sample index 600. The DWT output for this signal clears that the CD_1 value for bus 3 shifts from nearly nil to 0.218504872286151 Pu at 601 sampling time, while in bus 4 the corresponding value increases as the highest value to 0.003396630715803 Pu.

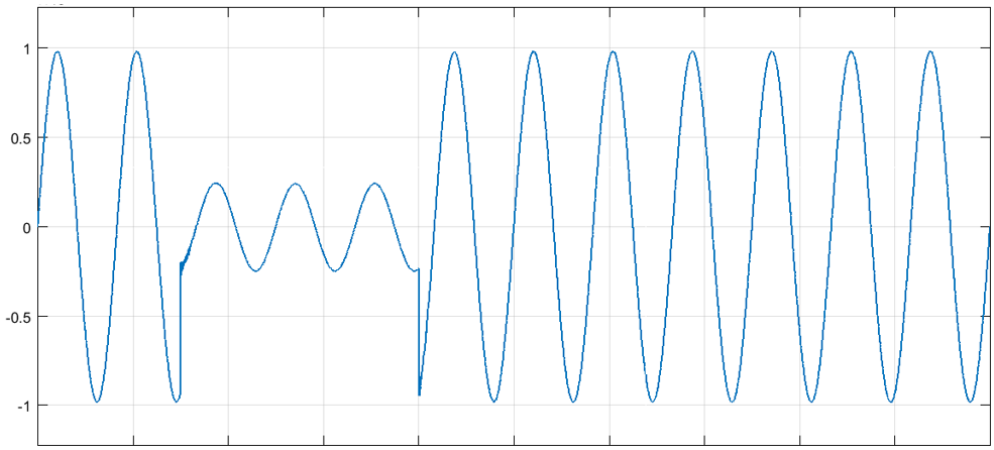
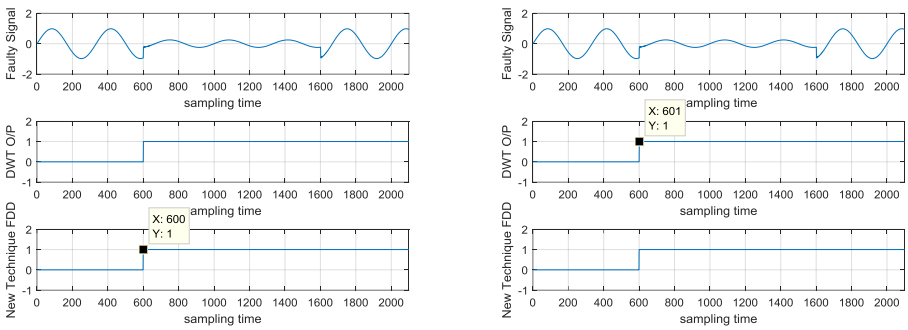


Fig. 4.17. Voltage sag faulty signal.

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 surely with sampling time 600 and 601 for proposed data fusion technique and DWT respectively as shown in next figure.



(a) new technique fault location (b) DWT fault location

Fig. 4.18. Output of new method FDD system for Voltage sag fault.

4.2.6 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 for used case 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 indicated in the next figure.

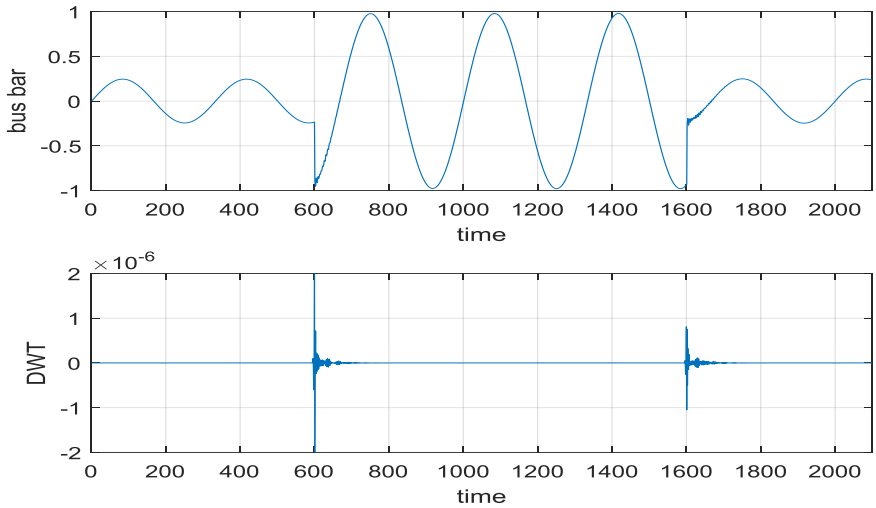


Fig. 4.19. Phase A on bus 3 and its corresponding DWT.

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

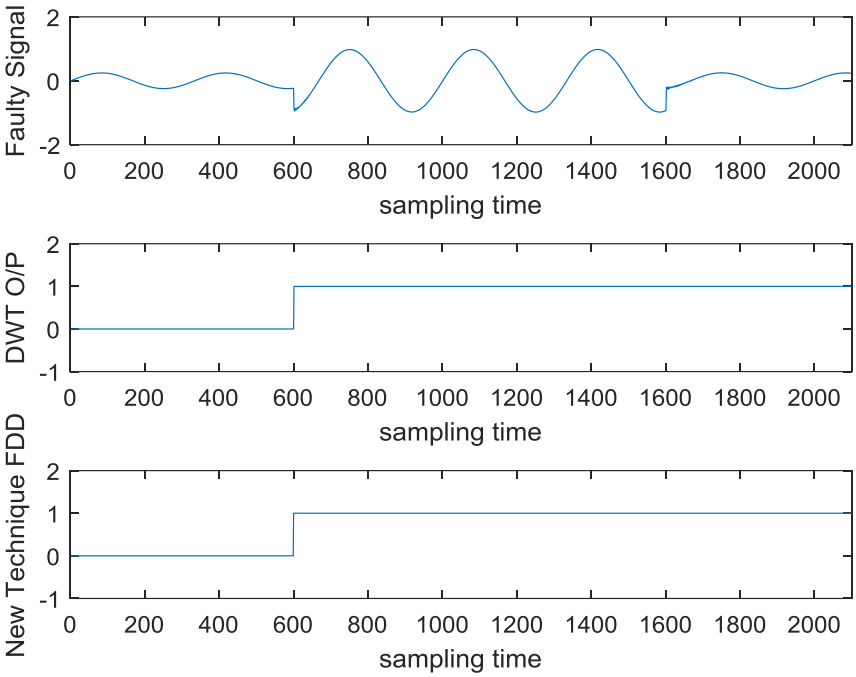


Fig. 4.20. Output of new method FDD system for Voltage swell fault.

4.3 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. The DWT output for this signal clears that the CD_1 value for bus 3 shifts from nearly nil to 0.172116008911899 Pu at 621 sampling time, while in bus 4 the corresponding value increases as the highest value to 0.003396630715803 Pu.

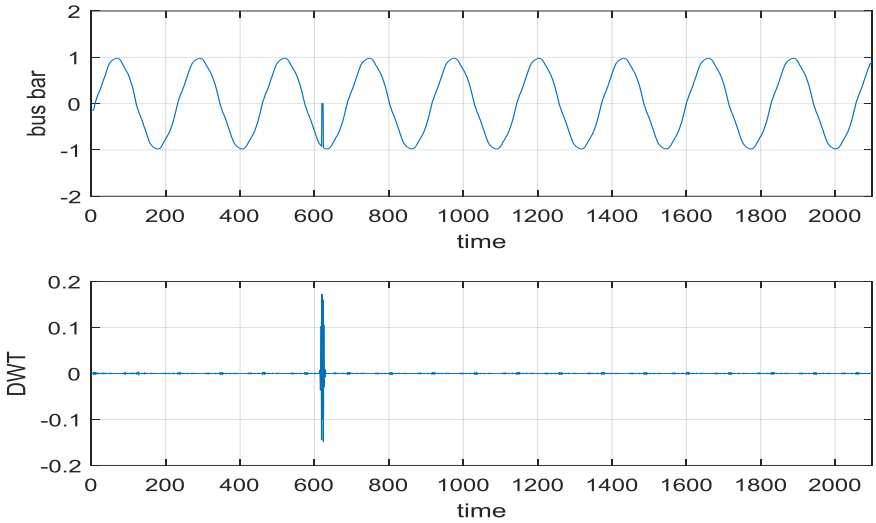


Fig. 4.21. Noisy signal and its DWT.

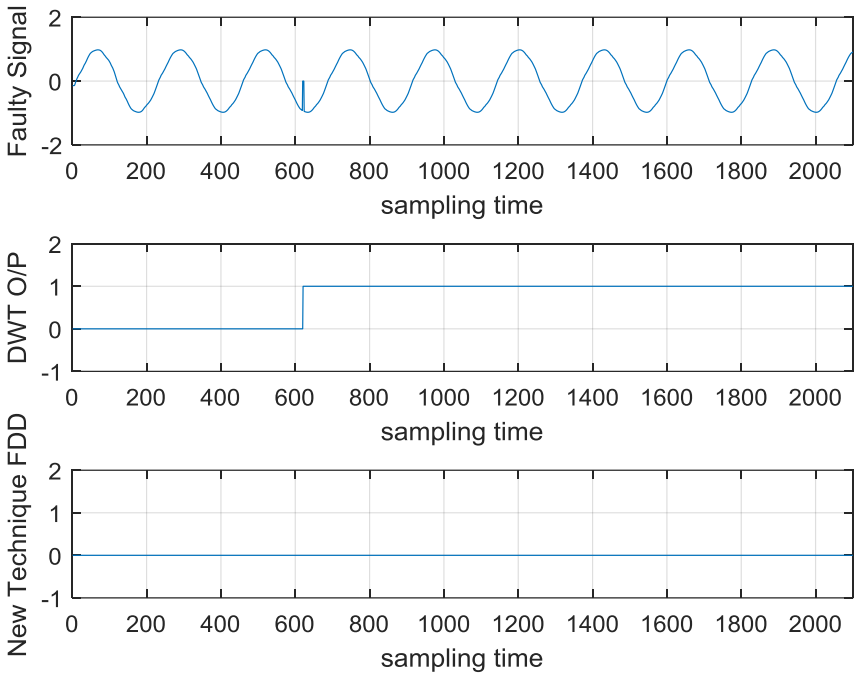


Fig. 4.22. Noisy signal, DWT, and new technique FDD output for noisy signal.

It is indicated from Figure 4.21 that the 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 technique has the capability to distinguish between them and when the signal is noisy the system keeps its normal action as declared in Figure 4.22.

CHAPTER 5

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORK

5.1 Conclusions

The objective of this chapter is to highlight the main results of the work done in this thesis and to provide suggestions for future research work in the area of FDD.

Some of the main conclusions are discussed below:

- A more precise FDD technique that can be used to differentiate between faulty and noisy signals on any smart grid was discussed.

- A comparison between the proposed technique and DWT were done in order to show the reliability and high efficiency of the proposed approach.

- The proposed technique was found to outperform DWT in two points, **first**, its fault area recognition velocity as there is very short delay time for detecting the fault. **Second**, the classifier can discriminate between noisy and faulty signals.

5.2 Proposed Future Work

The suggested technique could be conveniently implemented in the form of a MATLAB / SIMULINK module for the IEEE standard 14 bus system with correct feed-in parameters and determining the fault location index.

The suggestions of the future work can be summarized in next points as follows:

1- More experimental work is required for the study.

2- Trying other learner classifier such as support vector machine classifier or discriminant classifier to choose the suitable one.

3- This system can be processed with any relevant applications in realistic systems.

4- Finding other variables to enter to the system which seems a features to improve the efficiency of the system.

5- Making a comparison between data fusion technique and WT from many points of view such as complexity, time of processing, simulation time, and data storage.

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APPENDIX A: IEEE14 BUS SYSTEM

Table A.1: Line data – IEEE 14 bus system

Line number	From bus	To bus	Line impedance (p.u.)		Half line charging susceptance (p.u.)	MVA rating
			Resistance	Reactance		
1	1	2	0.01938	0.05917	0.02640	120
2	1	5	0.05403	0.22304	0.02190	65
3	2	3	0.04699	0.19797	0.01870	36
4	2	4	0.05811	0.17632	0.02460	65
5	2	5	0.05695	0.17388	0.01700	50
6	3	4	0.06701	0.17103	0.01730	65
7	4	5	0.01335	0.04211	0.00640	45
8	4	7	0	0.20912	0	55
9	4	9	0	0.55618	0	32
10	5	6	0	0.25202	0	45
11	6	11	0.09498	0.1989	0	18
12	6	12	0.12291	0.25581	0	32
13	6	13	0.06615	0.13027	0	32
14	7	8	0	0.17615	0	32
15	7	9	0	0.11001	0	32
16	9	10	0.03181	0.0845	0	32
17	9	14	0.12711	0.27038	0	32
18	10	11	0.08205	0.19207	0	12
19	12	13	0.22092	0.19988	0	12
20	13	14	0.17093	0.34802	0	12

Table A.2: Capacity and cost coefficients – IEEE 14 bus system

Generator number	P_i^{min} (MW)	P_i^{max} (MW)	a_i $(\$/(MWhr)^2)$	b_i $(\$/MWhr)$	c_i $(\$/hr)$
G_1	10	160	0.005	2.450	105.000
G_2	20	80	0.005	3.510	44.100
G_3	20	50	0.005	3.890	40.600

Table A.3: Transformer tap setting data – IEEE 14 bus system

From bus	To bus	Tap setting value (p.u.)
4	7	0.978
4	9	0.969
5	6	0.932

Table A.4: Bus data – IEEE 14 bus system

Bus number	Bus voltage		Generation		Load		Reactive power limits	
	Magnitude ($p.u.$)	Phase angle (degree)	Real power (MW)	Reactive power ($MVAR$)	Real power (MW)	Reactive power ($MVAR$)	Q_{min} ($MVAR$)	Q_{max} ($MVAR$)
1	1.060	0	114.17	-16.9	0	0	0	10
2	1.045	0	40.00	0	21.7	12.7	-42.0	50.0
3	1.010	0	0	0	94.2	19.1	23.4	40.0
4	1	0	0	0	47.8	-3.9	–	–
5	1	0	0	0	7.6	1.6	–	–
6	1	0	0	0	11.2	7.5	–	–
7	1	0	0	0	0	0	–	–
8	1	0	0	0	0	0	–	–
9	1	0	0	0	29.5	16.6	–	–
10	1	0	0	0	9.0	5.8	–	–
11	1	0	0	0	3.5	1.8	–	–
12	1	0	0	0	6.1	1.6	–	–
13	1	0	0	0	13.8	5.8	–	–
14	1	0	0	0	14.9	5.0	–	–

Table A.5: Shunt capacitor data – IEEE 14 bus system

Bus number	Susceptance ($p.u.$)
9	0.19

ملخص البحث

الرسالة المقدمة من الباحث تناولت نظام متميز حيث يُمَكن انظمة الحماية الكهربية فى الشبكات من الاكتشاف السريع والتشخيص الجيد للاخطاء فى المنظومة الكهربية. حيث تم اقتراح طرق جديدة لتحديد الاخطاء معتمدة على أنظمة انصهار البيانات وطرق استخدامها في الشبكات الذكية حيث تعمل علي اندماج المعلومات من المصادر او المدخلات المختلفة وذلك للخروج بخصائص جديدة وبصفات مميزة تعطينا صورة أوضح عن النظام. ويمكن استخدام أنظمة انصهار البيانات فى حالة فقد احد المدخلات او اكثر حيث يمكن للنظام ان يتوقع ويستنتج القراءات بناء" علي القراءات السابقة. المحتوي الكلي للرسالة يحتوي على طريقة جديدة باستخدام إنصهار بيانات محسنة للتصميم الامثل والتشغيل فى إكتشاف تشخيص الاخطاء. أيضا تم استخدام (DWT) حيث تبين من النتائج انه به عيب من خلال عدم تمييزه للاشارة ما بين الاخطاء و الضجيج الموجود بالشبكة. النظام الجديد بالرسالة المقدم من الباحث تغلب على معظم العيوب السابقة من خلال المقدرة على التمييز بين الاخطاء و الضجيج. النظام المستخدم بانصهار البيانات وذلك من خلال القراءات بين الجهد والقدرة زادت من دقة القرارات لتصنيف وتحديد اماكن الاخطاء بالشبكة الكهربية حيث تم المحاكاة للنظام من خلال حدوث الاخطاء فى العديد من الاماكن المحتمل حدوث الاخطاء بها. تم استخدام IEEE standard 14-bus system لتنفذ عليه جميع الحالات التي تم سردها بالرسالة من اخطاء كهربية وذلك لتقييم الطريقة المقدمة من الباحث وأيضا تم تنفيذ العديد من الحالات سواء اخطاء كهربية اوضجيج لتبين الكفاءة والدقة العالية للنظام المستخدم.

وتشتمل الرسالة علي خمسه فصول تفاصيلها فيما يلى:

الفصل الاول: يحتوى على مقدمة عامة عن موضوع البحث، وكذلك يوضح الأهداف المختلفه للرسالة ومحتوياتها.

الفصل الثاني: يقدم هذا الفصل نظرة عامة على الطرق المستخدمه فى إيجاد وتحديد الاخطاء فى الشبكات الكهربية , وأيضا كيفية تحديد وتصنيف وإيجاد مكان الخطأ بدقة تم عرضه بطريقه مفصلة حيث تم تحديد الخطأ عن طريق ثلاث طرق معتمده على (مجال الزمن – مجال التردد – مجال الزمن والتردد معا), ثم تم تصنيف الطرق لاكتشاف الاخطاء من خلال اربع طرق (الطرق التقليدية – الذكاء الإصطناعي – الطرق الهجينة – الطرق المنطقية المتدفقة).

الفصل الثالث: يتناول هذا الفصل طرق تقنية إنصهار البيانات وحصر أهم الدراسات والابحاث السابقه فى هذا المجال، حيث تم تقسيمها الي اربع انواع مختلفة اولا: طبيعة ونوع المعلومات الداخلة والخارجة للطريقة المستخدمة, ثانيا العلاقة بين مصادر الدخل حيث كونها تكاملية او زائدة او تعاونية, ثالثا طريقة الهيكلة للشبكة من حيث كونها مركزية أو لا مركزية أو موزعة, رابعا الطريقة الاخيرة معتمدة على خمس مستويات وتم تقسيمهم الي المستويات السفلى والستويات العليا.

الفصل الرابع: فى هذا الفصل تم توضيح دراسة المحاكاة والنتائج المترتبة عليها وتم رسم المخطط التوضيحي للطريقة المستخدمه فى الرسالة, وتم تقسيم الاخطاء التي يمكن ان تحدث فى الشبكة الي متماثلة وغير متماثلة, أولا حدوث دائرة قصر بين الفازة و الارضي بأنواعها المختلفة, او فى حالة هبوط فى الجهد لفترة معينة, او فى حالة زيادة فى الجهد لفترة أخري, أخيرا دراسة التأثيرات الخارجية على الشبكة الكهربية.

الفصل الخامس: يحتوي هذا الفصل علي عرض لأهم الإستنتاجات التي تم التوصل اليها من خلال هذة الرسالة، كما يتضمن بعض المقترحات للنقاط التي يتعين دراستها في المستقبل.

تقنية إنصهار بيانات محسنة للتصميم الأمثل والتشغيل لأنظمة إكتشاف الأخطاء

رسالة مقدمة من

المهندس/ أيمن سليمان سلمي محمد

إلى كلية الهندسة ببنها – جامعة بنها

كجزء من متطلبات الحصول على درجة دكتوراه الفلسفة في العلوم الهندسية فى الهندسة الكهربية من كلية الهندسة ببنها

أعتمدت و أجيزت من السادة الممتحنين

أ.د./ رزق محمد السيد حمودة **(ممتحناً خارجيا ورئيساً)**

أستاذ متفرغ بقسم الهندسة الكهربية، كليه الهندسة ، جامعة عين شمس

وعميد المعهد الكندى العالي للهندسة باالسادس من اكتوبر. .....

أ.د./ محمد الشيمى محمود بخيت **(ممتحناً خارجيا وعضواً)**

أستاذ بقسم الهندسة الكهربية، كليه الهندسة ، جامعة عين شمس.

.....

أ.د./ غادة محمد عامر **(رئيس لجنه الإشراف و وعضواً)**

أستاذ بقسم الهندسة الكهربية، كليه الهندسة ببنها , جامعة بنها

.....

اعتمدت من قسم الهندسة الكهربية **(رئيس القسم)**

أ.د./ أيمن على أحمد ندا

.....

اعتمدت من الدراسات العليا **(وكيل الكلية للدراسات العليا)**

أ.د./ غادة محمد عامر

.....

اعتمدت من كلية الهندسة ببنها **(عميد الكلية)**

أ.د./ عارف محمد سليمان

.....

جامعة بنها

كلية الهندسة ببنها

قسم الهندسة الكهربية

تقنية إنصهار بيانات محسنة للتصميم الأمثل والتشغيل لأنظمة إكتشاف الأخطاء

رسالة مقدمة كجزء من متطلبات الحصول على درجة دكتوراه الفلسفة في العلوم الهندسية في الهندسة الكهربية

اعداد

المهندس/ أيمن سليمان سلمي محمد

ماجستير الهندسة و التكنولوجيا في الهندسة الكهربية

2014

المــشـرفــون

أ.د./ غادة محمد عامر

أستاذ بقسم الهندسة الكهربية

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