5-2022

AN INTELLIGENT PASSIVE ISLANDING DETECTION AND CLASSIFICATION SCHEME FOR A RADIAL DISTRIBUTION SYSTEM

Mohannad Khaleel Subhi Suleiman

جامعة الإمارات العربيـة المتحدة
United Arab Emirates University

MASTER THESIS NO. 2022: 44

College of Engineering

Department of Electrical and Communication Engineering

AN INTELLIGENT PASSIVE ISLANDING DETECTION AND CLASSIFICATION SCHEME FOR A RADIAL DISTRIBUTION SYSTEM

Mohannad Khaleel Subhi Suleiman

May 2022

United Arab Emirates University

College of Engineering

Department of Electrical and Communication Engineering

AN INTELLIGENT PASSIVE ISLANDING DETECTION AND CLASSIFICATION SCHEME FOR A RADIAL DISTRIBUTION SYSTEM

Mohannad Khaleel Subhi Suleiman

This thesis is submitted in partial fulfillment of the requirements
for the degree of Master of Science in Electrical Engineering

Under the supervision of Professor Hussain Shareef

May 2022

Declaration of Original Work

I, Mohannad Khaleel Subhi Suleiman, the undersigned, a graduate student at the United Arab Emirates University (UAEU) and the author of this thesis titled *"An Intelligent Passive Islanding Detection and Classification Scheme for A Radial Distribution System"* hereby solemnly declare that this is the original research work done by me under the supervision of Professor. Hussain Shareef in the College of Engineering at UAEU. This work has not previously been presented or published or formed the basis for the award of any academic degree, diploma, or a similar title at this or any other university. Any materials borrowed from other sources (whether published or unpublished) and relied upon or included in my thesis/dissertation have been properly cited and acknowledged in accordance with appropriate academic conventions. I further declare that there is no potential conflict of interest with respect to the research, data collection, authorship, presentation, and/or publication of this thesis.

Student’s Signature: ________________________ Date: 30 May, 2022

Approval of the Master Thesis

This Master Thesis is approved by the following Examining Committee Members

1) Advisor (Committee Chair): Hussain Shareef
   Title: Professor
   Department of Electrical and Communication Engineering
   College of Engineering
   Signature ______________________ Date 30 May, 2022

2) Member: Rachid Errouissi
   Title: Assistant Professor
   Department of Electrical and Communication Engineering
   College of Engineering
   Signature ______________________ Date 30 May, 2022

3) Member (External Examiner): Yasser Abdel-Rady I. Mohamed
   Title: Professor
   Department of Electrical and Computer Engineering Department
   Institution: University of Alberta, Canada
   Signature ______________________ Date 30 May, 2022

This Master Thesis is accepted by:

Acting Dean of the College of Engineering: Professor Mohammed Al-Marzouqi

Signature Mohamed AlMarzouqi Date August 12, 2022

Dean of the College of Graduate Studies: Professor Ali Al-Marzouqi

Signature Ali Hassan Date August 15, 2022

Abstract

Distributed generation (DG) provides users with a dependable and cost-effective source of electricity. These are directly connected to the distribution system at customer load locations. Integration of DG units into an existing system has significantly high importance due to its innumerable advantages. The high penetration level of distributed generation (DG) provides vast techno-economic and environmental benefits, such as high reliability, reduced total system losses, efficiency, low capital cost, abundant in nature, and low carbon emissions. However, one of the most challenges in microgrids (MG) is the island mode operations of DGs. the effective detection of islanding and rapid DG disconnection is essential to prevent safety problems and equipment damage. The most prevalent islanding protection scheme is based on passive techniques that cause no disruption to the system but have extensive nondetection zones. As a result, the thesis tries to design a simple and effective intelligent passive islanding detection approach using a CatBoost classifier, as well as features collected from three-phase voltages and instantaneous power per phase visible at the DG terminal. This approach enables initial features to be extracted using the Gabor transform (GT) technique. This signal processing (SP) technique illustrates the time-frequency representation of the signal, revealing several hidden features of the processed signals to be the input of the intelligent classifier.

A radial distribution system with two DG units was utilized to evaluate the effectiveness of the proposed islanding detection method. The effectiveness of the proposed islanding detection method was verified by comparing its results to those of other methods that use a random forest (RF) or a basic artificial neural network (ANN) as a classifier. This was accomplished through extensive simulations using the DIgSILENT Power Factory® software. Several measures are available, including accuracy (F1 Score), area under curve (AUC), and training time. The suggested technique has a classification accuracy of 97.1 percent for both islanded and non-islanded events. However, the RF and ANN classifiers' accuracies for islanding and non-islanding events, respectively, are proven to be 94.23 and 54.8 percent, respectively. In terms of the training time, the ANN, RF, and CatBoost classifiers have training times of 1.4 seconds, 1.21 seconds, and 0.88 seconds, respectively. The detection time for all methods was less than one cycle. These metrics demonstrate that the suggested strategy is robust and capable of distinguishing between the islanding event and other system disruptions.

Keywords: Distributed Generation, Inverters, Micro-grids, Islanding Detection, Gabor Transform.

Title and Abstract (in Arabic)

نظام ذكي للكشف عن التجزر وتصنيفه لنظام التوزيع الشعاعي

الملخص

توفر موزعات القدرة للمستخدمين مصدرا معتمد للكهرباء ذو تكلفة منخفضة. وهذه الموزعات متصلة مباشرة بنظام التوزيع في مواقع تحميل العملاء. ويتسم إدماج وحدات التوليد الموزعة في نظام قائم بأهمية كبيرة بسبب مزاياه التي لا تعد ولا تحصى. ويوفر مستوى الاختراق المرتفع لموزعات القدرة فوائد تقنية - اقتصادية وبيئية كبيرة، مثل إرتفاع الموثوقية، وانخفاض مجموع خسائر النظم، والكفاءة، وانخفاض تكلفة رأس المال، والوفرة في الطبيعة، والانبعاثات الكربونية المنخفضة. ومع ذلك، فإن أحد أكبر التحديات في الشبكات المصغرة هي عمليات وضع الجزر التي تقوم بها هذه الموزعات. يعد الكشف الفعال للتجزر بسرعة أمر ضروري لمنع مشاكل السلامة والتلف في المعدات. وتعتمد أكثر خطط حماية الجزر انتشارا على تقنيات سلبية لا تسبب أي تعطيل للنظام ولكن توجد بها مناطق واسعة لا يمكن اكتشافها. ونتيجة تحاول الأطروحة تصميم طريقة ذكية وفعالة للكشف عن الجزر السلبية باستخدام مصنف CatBoost. بالإضافة إلى الميزات التي تم جمعها من الفولتية ثلاثية الطور والطاقة اللحظية لكل طورالتي يمكن قياسها في محطات موزعات القدرة. يتيح هذا النهج إمكانية استخراج الميزات الأولية باستخدام تقنية تحويل غابور. توضح تقنية معالجة الإشارة هذه تمثيل التردد الزمني للإشارة، وتكشف عن العديد من الميزات المخفية للإشارات المعالجة لتكون مدخلات المصنف الذكي.

تم استخدام نظام توزيع شعاعي مع وحدتي موزعات القدرة لتقييم فعالية الطريقة المقترحة للكشف عن الجزر. تم التحقق من فعالية الطريقة المقترحة من خلال مقارنة نتائجها بنتائج الطرق الأخرى التي تستخدم غابة عشوائية أو شبكة عصبية اصطناعية أساسية كمصنف. تم تحقيق ذلك من خلال عمليات محاكاة مكثفة باستخدام برنامجDIgSILENT Power Factory (®). تتوفر العديد من المقاييس، بما في ذلك الدقة والمنطقة الواقعة تحت المنحنى ووقت التدريب. تتميز التقنية المقترحة بدقة تصنيف تبلغ 97.1 في المائة لكل من الأحداث المقامة على التجزر وغير المقامة على التجزر. ومع ذلك، فقد ثبت أن دقة مصنفات (RF) و(ANN) لأحداث التجزر وغير التجزر، كانت 94.23 و 54.8 في المائة، على التوالي. فيما يتعلق بوقت التدريب، تتمتع مصنفات (ANN)، (RF) و (CatBoost) بأوقات تدريب تبلغ 1.4 ثانية و 1.21 ثانية و 0.88 ثانية على التوالي. كان وقت الكشف لجميع الطرق أقل من دورة واحدة. توضح هذه المقاييس أن

الاستراتيجية المقترحة متينة وقادرة على التمييز بين حدث التجزر واضطرابات النظام الأخرى.

مفاهيم البحث الرئيسية: موزعات القدرة، المحول، الشبكات المصغرة، كشف التجزر، تحويل غابور.

Acknowledgements

First and foremost, praise is to Almighty Allah for all His blessings for giving me perseverance and good health to finish this master's project.

I would like to express my deep sense of profound gratitude to my honorable and esteemed guide, Dr. Hussain Shareef, for his wise counsel, support, and direction. Over time he has introduced me to the academic world. His perspective on my work has inspired me to go on. I am glad to work with him. This thesis would not have been completed on time if it hadn't been for his tireless support, leadership, and faith in my talents.

Last but not least, my heartfelt appreciation and gratitude go out to all of my family members; my father's soul, my mother, brothers, and sisters, and especially "who aided me along the way by giving me all of the necessities, Special thanks go to my friends, who supported me with all of their efforts and pushed me to achieve my goal with tenacity.

Dedication

To my father's late soul, in loving memory

To my mother for her endless Love, Support & Encouragement

To my sisters & brothers who inspired me all the time

To my friends who motivated me for a long time

Table of Contents

List of Tables

List of Figures

List of Abbreviations

AFD	Active Frequency Drift
AI	Artificial Intelligent
ANFIS	Adaptive Neuro-Fuzzy Interference System
ANN	Artificial Neural Network
AVR	Automatic Voltage Regulator
CCP	Common Coupling Point
CF	Correlation Factor
CWT	Continuous Wavelet Transform
DG	Distributed Generation
DMS	Distribution Management System
DT	Decision Tree
DWT	Discrete Wavelet Transform
FFT	Fast Fourier Transforms
FL	Fuzzy Logic
FLC	Fuzzy Logic Control
GC	Gabor Coefficient
GM	Gabor Matrix
GT	Gabor Transform
IC	Intelligent Classifier
IM-SMS	Improved- Slip-Mode Frequency Shift
IP	Instantaneous Power
MLP	Multilayer Perception
MG	Microgrid

MRA	Multi-Resolution Analysis
NDZ	Non-Detection Zones
PCC	Point of Common Coupling
PNN	Probabilistic Neural Network
POI	Probability of Islanding
PSO	Particle Swarm Optimizations
PV	Photovoltaics
RBFNN	Radial Basis Neural Network
RF	Random Forest
ROCOF	Rate of Change of Frequency
ROCOV	Rate of Change of Voltage
SCADA	Supervisory Control and Data Acquisition
SFS	Sandia Frequency Shift
SMS	Slip-Mode Frequency Shift
SP	Signal Processing
SVM	Support Vector Machines
SVS	Sandia Voltage Shift
T&D	Transmission And Distribution
TFD	Time-Frequency Distribution
THD	Total Harmonic Distortion
UFLS	Under Frequency Load Shedding
UFP/OFP	Under/Over Frequency Protection
UVLS	Under Voltage Load Shedding
UVP/OVP	Under/Over Voltage Protection

VSC	Voltage-Source Control
VSM	Voltage Stability Margin
VU	Voltage Unbalance
WPT	Wavelet Packet Transform
WT	Wavelet Transform

List of Symbols

A	Data Set
C	Discrete Gabor Coefficients
C_n	Classes
D	Index Values Of Gabor Coefficient
f	Frequency
g	Base Predictor
$g(\tau)$	Gaussian Function
h	Basis Functions
H	Train Function
Hz	Hertz
i(t)	Instantaneous Current
I	Maximum Values of Instantaneous Current
k	Phase Number
kV	Kilo Volts
kW	Kilo Watts
L	Point Window
L	Smooth Loss Function
$\mathcal{L}$	Expected Loss
M	Number Of Samples in Time Domain
ms	Millisecond
MVA	Mega Volt Ampere
MVAR	Mega Volt Ampere Reactive
MW	Mega Watt

n	Number of Sample Points
N	Number of Samples in Frequency Domains
N_s	Sampling Rate in Each Period
$P(\mathrm{t})$	Instantaneous Active Power
P_e	Electric Power in Generator
P_{gen}	Generator Power
P_{gi}	Generated Active Power
R	Maximum Values of The Absolute Value of Gabor Matrix
r	Residuals
rand	Random Value Obtained from a Standard Normal Distribution
t	Sliding Variable of Time
up and *low*	Upper and Lower Boundaries
$v(\mathrm{t})$	Instantaneous Voltage
V	Maximum Values of Instantaneous Voltage
Vdc	Direct Current Voltage
$\mathrm{w}(\tau)$	Window Function
X	Feature Vector
Ydgi	Outputs of the Individual Classifier
Youtput	Final Output of the Decision Making
σ	Specific Order
$\bar{E}$	Root Mean
ΔP	Power Imbalance
ΔM	Sampling Time Intervals

ΔN	Sampling Frequency Intervals
γ	Dual Basis of h
τ	Signal Function in the Time-Domain
ω	Angular Frequency

Chapter 1: Introduction

1.1 Research Background

Distribution systems have traditionally relied on power from upstream sources that are connected to the bulk transmission system to supply customers with electricity. Renewable resources are increasingly being employed in the distribution system to fulfill the growing electricity demand and tackle the global heating dilemma caused by traditional energy sources like coal, oil, and natural gas. These small-scale resources are called distributed generation and are typically in the range of a few kW to a few MWs and have numerous advantages, including lower air pollution, enhanced dependability, increased efficiency, prevention of transmission and distribution (T&D) capacity improvements, improved power quality, and reduced T&D line losses. As shown in Figure 1.1 and Figure 1.2, there is a significant difference between traditional and multiple embedded distribution systems, where additional DG is frequently connected near the local load.

Traditional methods for energy production and distribution are therefore evolving, posing new difficulties for maintaining the grid's equilibrium. Figure 1.3 illustrates one of the most important challenges with these integrations: the islanding condition, which can occur intentionally or unintentionally due to the abrupt disconnection of the grid in some abnormal scenarios. On the other hand, the DG ensures that the power supply to the local loads is maintained. When the system operates in island mode, the active part of the distribution system should sense the disconnection from the main grid and fast DG removal are crucial to avoid equipment failure, grid safety issues, as well as potential dangers to personnel safety.

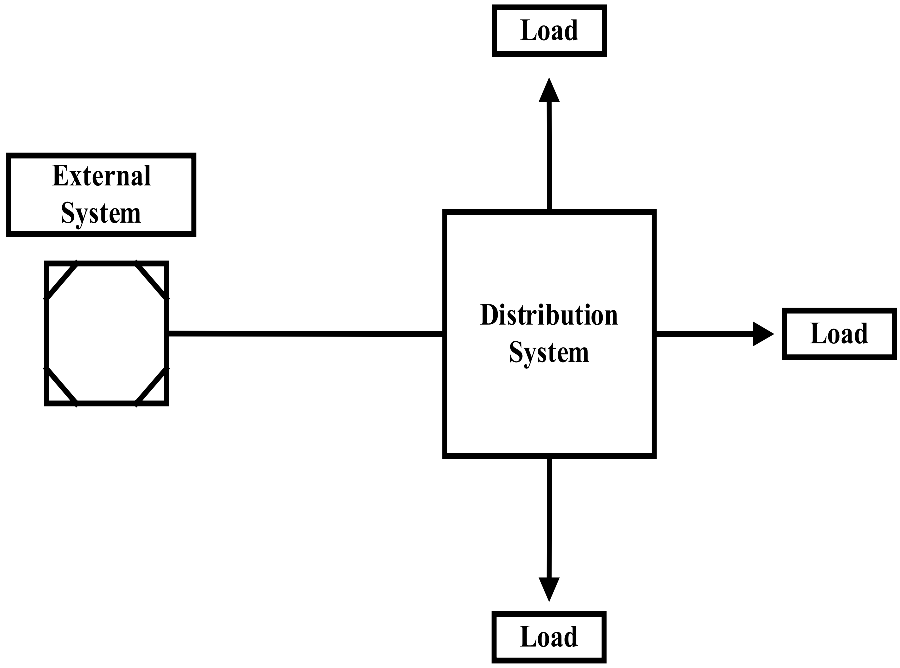


Figure 1.1: Conventional distribution system

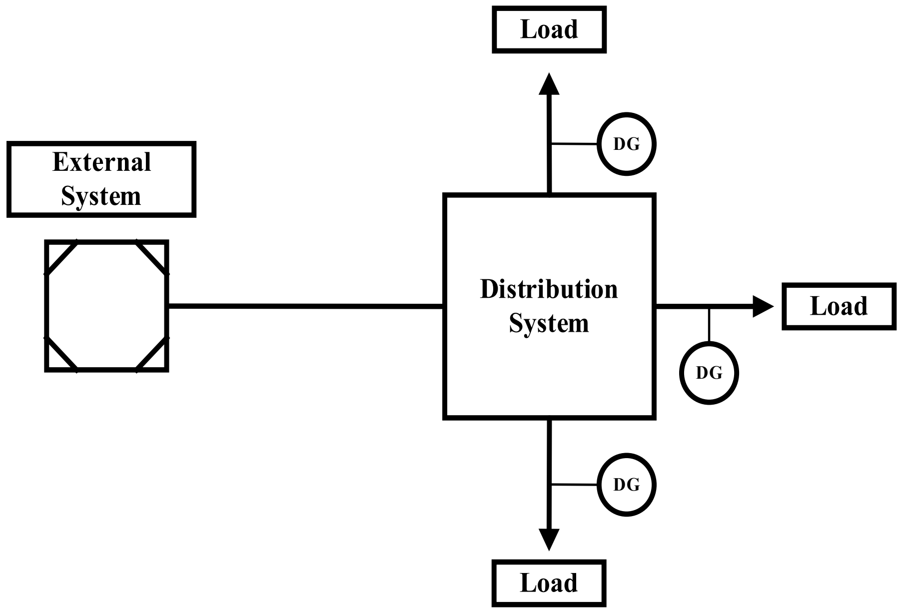


Figure 1.2: Distributed generation system

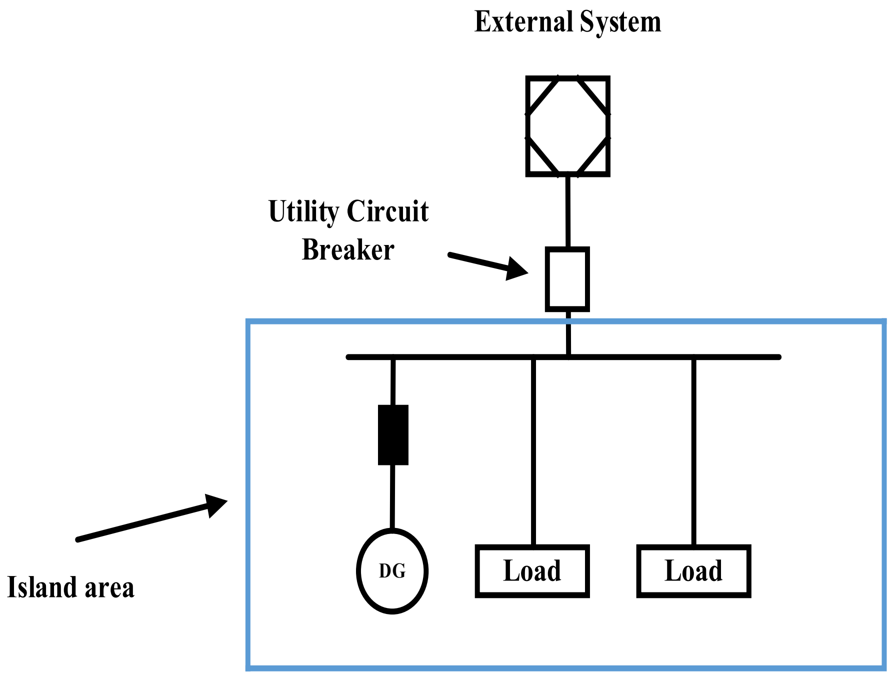


Figure 1.3: Island mode

1.2 Problem Statement

Since islanding mode can take place in two ways: intentionally and unintentionally. The first case is applied locally in the MG for maintenance such as live working or economic purposes, and it does not pose any issue as the plant controller is aware of the situation. However, unintentional islanding is problematic because it is performed by an external agent and the MG plant controller is not aware of this issue [1]. In that case, the utility system will continue to be powered if the local generators keep bulking out power. Then there will be a lot of problems that affect power quality, voltage, and frequency stability, as well as personnel safety, as they may be at risk of electrocution if they attempt to control the utility grid while it is supposed to be unplugged. Hence, the power system should be disconnected within 2 seconds according to various islanding standards like IEC 62116, IEEE Std. 929-2000, IEEE Std. 1547-2003 and the operation of DG should be stopped immediately [2].

Consequently, the current research aims to establish a simple approach that can easily assess the islanding state by distinguishing between systemic islanding and non-islanding scenarios. The islanding state can be accurately detected using numerous methods, but the most cost-effective and efficient method relies on the local method combined with signal processing tools and artificial intelligence (AI). This method is preferred since it requires a more accurate online detection to monitor the system's state and is less complicated. It is usually more efficient in terms of computation and accuracy, and it is usually more reliable than other methods. Signal processing (SP) and neural networks (NN) are the most prevalent techniques utilized nowadays. Various contributions based on these methodologies will be discussed in the next chapter.

1.3 Objective of the Research

The objectives of the research are as follows:

i. To develop a reliable and accurate method of islanding detection and classification that can accurately identify the islanding condition.

ii. To evaluate and compare the suggested islanding detection scheme with the currently available technique.

1.4 The Scope of the Research

The primary objective of this research is the creation of an islanding detecting algorithm. Currently, no previous research has used Gabor feature extraction based on the CatBoost algorithm in power system islanding detection. The Gabor Transform's distinct features, along with CatBoost as the classifier, can be used to create a robust and effective islanding detection scheme. The suggested islanding detection technique is validated by simulating a radial distribution system with two identical DG units in

DIgSILENT Power Factory® software. Furthermore, the performance evaluation approach is employed to evaluate the effectiveness and accuracy of the proposed islanding detection algorithm. This review contains a comparison of certain methods based on Random Forest (RF) and Artificial neural network (ANN) algorithm, as well as the use of various metrics to validate the proposed method's prediction accuracy.

1.5 Organization of the Thesis

This thesis is divided into five chapters, which are ordered as follows:

Chapter 1 presents the general idea of the problem related to this work as well as a discussion of the most effective strategy for solving the problem. Additionally, it provides the proposed contribution briefly and an explanation of the primary goal of the research.

Chapter 2 gives an overview of the islanding detection methods, and various islanding detection methods are discussed in detail, including their advantages and disadvantages.

Chapter 3 discusses the development of the proposed islanding detection technique, which was implemented in the proposed system to identify islanding events using the GT method.

Chapter 4 provides an analysis of the results acquired from the development of the islanding detection technique.

Chapter 5 provides the conclusion on the most significant accomplishment of the study and an investigation within the scope of the research performed and documented in this thesis. At the end of the chapter, a few suggested directions for further study are mentioned.

Chapter 2: Literature Review

In this chapter, numerous islanding detection methods are defined and discussed. Existing methods and their advantages and disadvantages are also reviewed. Then based on the review, the research gap related to islanding detection is identified.

2.1 Islanding Detection Methods

The islanding detection technique is used to detect the formation of MG due to the operation of the Common Coupling Point's circuit breaker when the DG is disconnected from the main grid but continues to feed the connected load. According to IEEE 929-1988 and IEEE 1547- 2003 standards, the photovoltaic system and other distribution resources must be disconnected once it is islanded with a maximum delay of 2 seconds for any unintentional islanding condition [3]. Thus, a variety of methods are proposed and broadly classified into two categories namely, remote and local methods as shown in Figure 2.1.

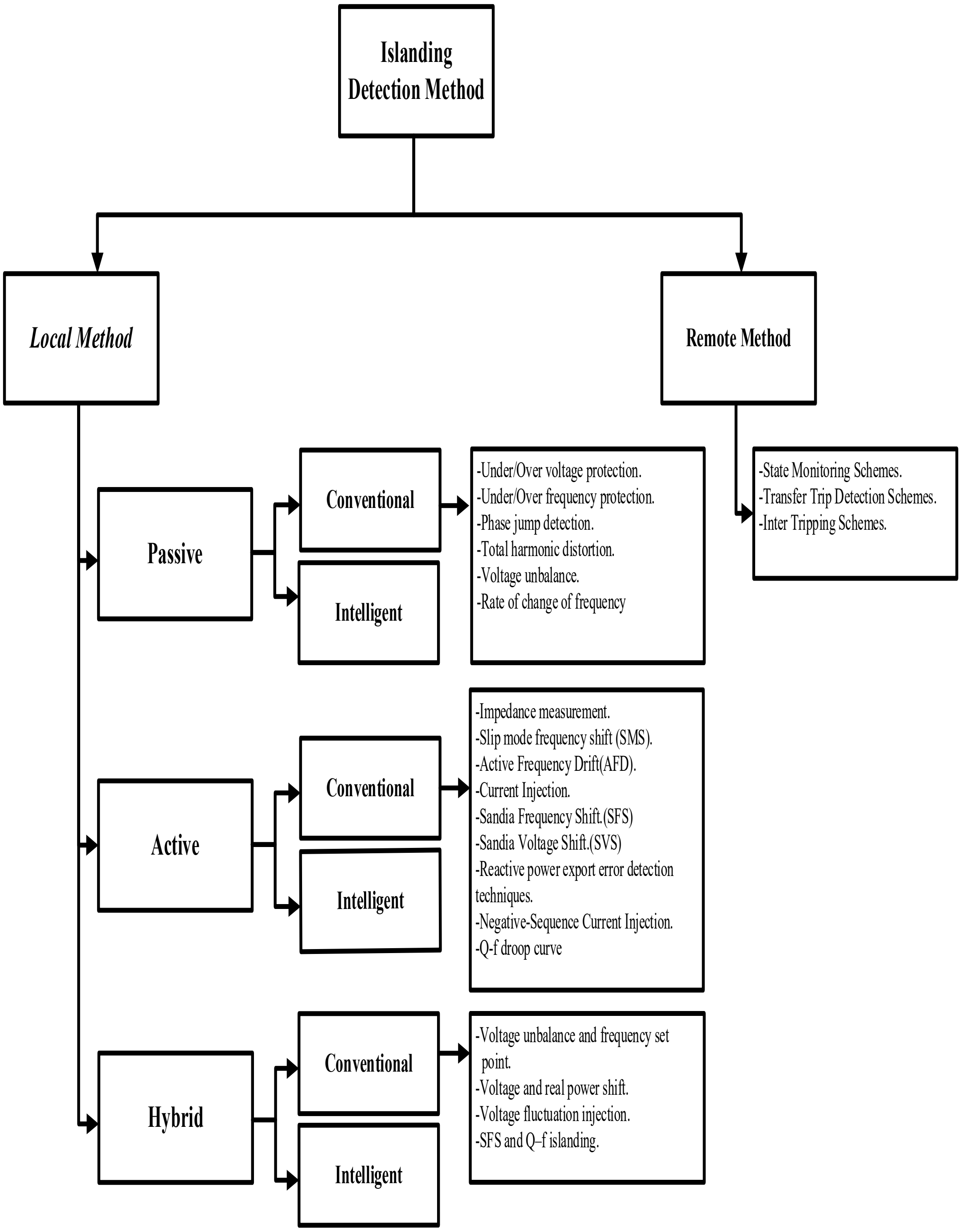


Figure 2.1: Classification of the islanding detection techniques

Remote approaches identify the islanding by aggregating signal information from the MG side, and these methods are further categorized as status monitoring, transfer trip detection, and inter-tripping systems. Meanwhile, the local islanding detection method is concerned with the MG side. The local methods are further classified as active, passive, or hybrid method. The details of all approaches are clarified and evaluated in the following subsections.

2.1.1 Central Islanding Detection Methods

Remote techniques rely on communication between DGs and utility circuit breakers via a central control unit and monitoring system, as shown in Figure 2.2. The central control receives status signals from the circuit breakers via a communication channel, such as an optical fiber network. These include fiber optic, private or leased digital networks, analog phone lines, digital phone lines, power line carrier, wireless radio, and two-wire transmission lines. Following that, the central controller determines the islanding status and communicates the alarm to the necessary DGs that comprise the island. They are free of non-detection zone concerns and so deemed robust for islanding detection. However, implementing these strategies requires significant expenditure, particularly at the infrastructural level.

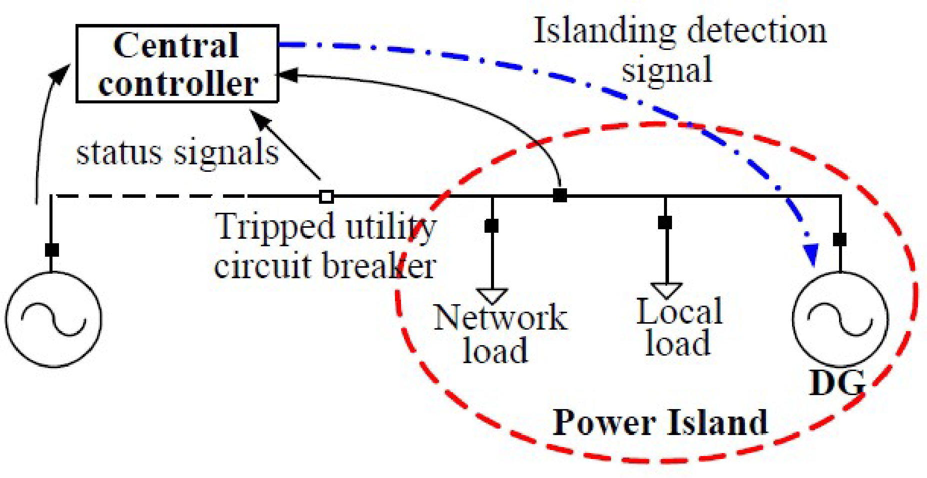


Figure 2.2: Central islanding detection technique [4]

2.1.2 State Monitoring Scheme

System state monitoring is a technique for determining the state of the system from a power system network model using a limited number of state measurements. This method is commonly thought to be a function of the distribution management system (DMS), which is a form of supervisory control and data acquisition (SCADA) system. Generally, SCADA systems use a wide communications network and sensors to control and monitor the state of a grid-connected equipment parameter such as voltage and frequency, allowing a fast response to contingencies that may arise in the grid and easing islanding detection. When the grid is disconnected, a series of alarms are activated for the disconnection of the DGs [5], in which the information is sent through a communication channel to a central station. If the parameters (frequency and voltage) cannot be detected from the disconnected area, the occurrence of islanding is detected. This method effectively detects unintentional islanding if the system is properly instrumented and controlled. However, the cost of implementation is expensive because each DG installed in the system requires separate instrumentation and communication equipment [2]. For example, as detailed in [7], the SCADA system can be used to monitor the auxiliary contacts on all circuit breakers positioned between the primary source of generation and the DG units. In [3], the SCADA-based method uses the placement of voltage sensors at the location where DG is connected and integration of those sensors into the SCADA system for monitoring and alarming the PV system to disconnect in case of islanding. With the high number of DGs connected to the grid, real-time monitoring of voltage for each generator in the distribution grid can be a cumbersome process.

2.1.3 Transfer Trip Detection Scheme

The transfer trip detection approach necessitates the monitoring and connection of all circuit breakers and the DG to be monitored and connected directly to the DG control or via a central substation SCADA system. When a disconnection is detected at the substation, the transfer trip system assesses which parts are islanded and generates an appropriate signal to the DGs, instructing them to either continue operating or shut down. Each transfer trip signal will require its own point-to-point communications circuit since devices are installed in geographically separate locations. Once the transfer trip signal is received at the generator, the local breaker will be opened, and the generator will be taken off-line. For cases where multiple isolation devices must operate to form an island, special logic schemes must be used to determine the presence of the island [9]. For example, as detailed in [10], Figure 2.3 illustrates the fundamental concept of the transfer trip scheme, which continuously monitors the status of all circuit breakers and reclosers capable of islanding a DG system. When a disconnection is discovered at the substation, signals from the central algorithm are transmitted to the trip inverter in the unintentionally islanded area. This central algorithm is used to check the islanding area when the switching operator creates a disconnection between the substations.

2.1.4 Intertripping Systems

Theoretically, inertripping is distinct from central control schemes. Intertripping does not operate based on the measurement of any electrical parameter. The method detects the opening of contact at the points of disconnection and transmits the signal to all generation sites that support the respective island zones. Intertripping generally relies on the communication between the sensors and generating units through communication channels. It can be classified into wired cable and non-wired. These techniques have higher reliability and provide accurate solutions but are uneconomical [11].

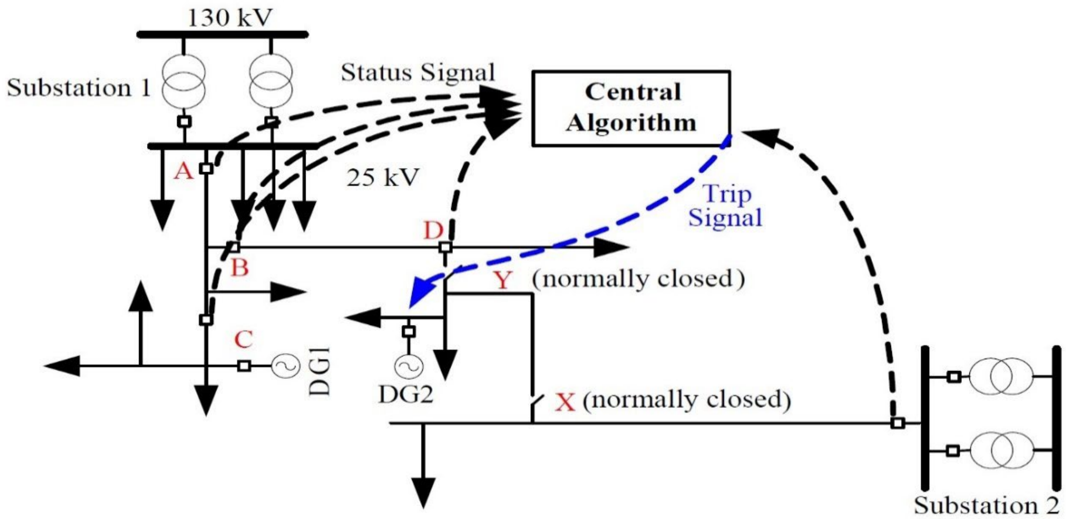


Figure 2.3: Transfer trip scheme [10]

These three strategies are employed because they have proven to be reliable. The reviews indicate that remote control strategies are preferred because they avoid nondetection zones (NDZs), a state of the system in which the power consumed by the load nearly matches the power generated by the DGs, and there is no impact on power quality or system transient response. These remote-control methods are also not influenced by the number of inverter interfaces, size of the system, type of generator, and penetration level [4]. However, the primary disadvantages of these remote techniques originate from their high implementation costs, which are exacerbated when used in small-scale networks that require an initial communication infrastructure with a utility. As a result, some researchers are concentrating their efforts on developing and implementing an islanding detection algorithm utilizing a local method. Table 2.1 summarizes the remote schemes for islanding detection.

Table 2.1: Summarization of remote islanding detection techniques

Methods	Advantages	Disadvantages	Effectiveness In Multiply Inverter Cases
State Monitoring Scheme (Scada System)	Include All DGs Avert NDZ.	Slow detection time, especially under the condition of a busy system. High investment cost. Maintenance challenges.	High effective.
Transfer Trip Scheme	Avert NDZ.	Complexity cost. Continuous relocation or updates.	High effective.
Power Line Carrier Communication	The simplicity of control. Reliability.	Uneconomical for low-density DG systems.	High effective.
Signal Produced by Disconnect	Allowing additional Control to DGs by the main Grid. Avert NDZ.	large amount of investment.	High effective.

2.2 Local Islanding Detection Schemes

Conventional techniques require the measurements at the DG site, without any communication infrastructure, and collect signal information such as voltage, frequency, harmonic distortion, and current on the DG site at the point of common coupling (PCC) with the utility grid. When the distribution system is islanded, these parameters vary dramatically depending on the power mismatch between the system and the DG. These local methods are sometimes referred to as "traditional methods" or "conventional methods".

2.2.1 Passive Techniques

Passive islanding detection approaches include voltage under/over protection (UVP/OVP), frequency under/over protection (UFP/OFP), phase jump detection, total harmonic distortion (THD), voltage imbalance (VU), and rate of change of frequency. Even while these passive parameters cannot deviate further in grid-connected mode, they do so when the system is islanded and can therefore be utilized to detect islanding [12].

A distinction is made between islanding and grid-connected modes based on the threshold values assigned to each of these variables. To distinguish the islanding event from other system disturbances, special care must be used when determining the threshold value. Figure 2.4 shows the detection procedure for passive approaches. For instance, [13] suggested an islanding detection scheme based on a combination of two conventional variables, namely, VU and THD of the current, which allowed it to effectively detect the islanding event without modifying the variation of DG loading. Reference [14] studied the impact of DG interface control on islanding detection and NDZ of OVP/UVP and OFP/UFP by utilizing constant current, constant P-V, and constant P-Q interface controls. Study presented in [15] compared and analyzed three different passive anti islanding methods namely Under Voltage (UOV), Under/Over Frequency (UOF/OUF), and the Positive Sequence Impedance method. It was observed that the positive sequence impedance method has the quickest response of the three as far as islanding detection is concerned.

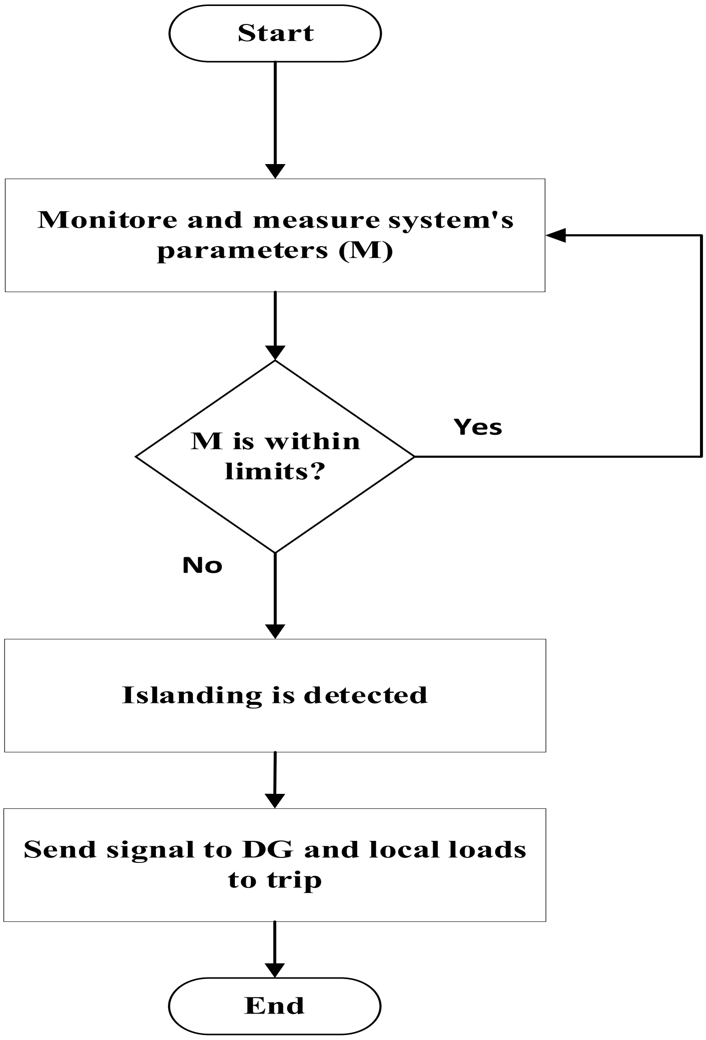


Figure 2.4: Working principle of passive islanding detection techniques

The instantaneous power theory and advanced power theory were used for islanding detection. For instance, in [16] the proposed method was based on instantaneous power calculation at the point of common coupling and was able to detect islanding conditions within a few sampling intervals. [17] proposed a technique based on the instantaneous active and reactive power at the point of common coupling (PCC) of the MG, which includes a natural gas-fired generator, a doubly-fed induction generator type wind generator, a solar generator, and some associated local loads. According to the PSCAD/EMTDC simulator, the performance of the proposed technique was tested in a variety of situations, including islanding circumstances for the various outputs of the MG, and fault conditions modifying the position, type, inception angle, and resistance of the fault. In [18], the synchronous reference frame method and conservative power theory were combined to extract relevant features from 3-phase electrical voltage signals in faulty situations for islanding event detection and recognition. Since this technique has been proved to produce a feature space that can be used by any nonlinear classifier, the cause of a fault can be determined in real time and with high accuracy. In [19] a new hybrid algorithm for passive islanding detection method was proposed based on combined changes of the rate of change of active power (ROCOAP) and rate of change of reactive power (ROCORP) at the PCC.

According to previous research, passive schemes are rapid and don't affect system power quality. Most parameters considered when selecting a passive islanding detection technique are accuracy, cost, and simplicity of implementation. Additionally, the passive approach is promoted as an efficient method for detecting islanding events in many grid-related scenarios. However, the primary disadvantage of passive approaches is their large NDZ, which results in the inability to detect the islanding scenario. So, various techniques to solve these issues were developed, which will be explored in the following paragraphs. The passive islanding strategies are summarized in Table 2.2.

Table 2.2: Summarization of passive islanding techniques

Methods	Advantages	Disadvantages	Effectiveness in Multiply Inverter Cases
UFP/OFP **UVP/OVP**	Easy to implement.	Slow detection time, large nondetection zone.	High effective.
Phase Jump Detection	NO power quality issue.	hard to identify threshold value. High error detection rate.	Not introduced.
THD	Easy to implement.	Large nondetection zone with high Q. Hard to identify the threshold value.	High effective.
VU	Low error detection rate. Simple implementation for three phase system.	Not applicable to single phase system.	Not introduced.
ROCOF	Small nondetection zone.	High error detection rate.	High effective.

2.2.2 Active Techniques

Recently, active techniques have been utilized by injecting a small perturbation to utility grids, with the grid's response deciding if it is islanded or not. The main philosophy of active islanding detection techniques is that a small perturbation results in a significant change in system parameters when a distribution system is islanded, whereas the change is negligible when the distribution system is still connected to the grid [14]. The detection process of active techniques is depicted in Figure 2.5. Impedance measurement, slip-mode frequency shift (SMS), active frequency drift (AFD), Sandia frequency shift (SFS), and Sandia voltage shift (SVS) are some of the well-known active ways to detect islanding. For instance, in [15] proposed method based on injecting a negative-sequence current through the VSC controller and detecting and quantifying the corresponding negative-sequence voltage at the point of common coupling of the VSC by enhanced phase-locked loop system which provides a high degree of noise immunity. Meanwhile, in [16], the popular slip mode frequency shift (SMS) and auto phase shift active islanding detection methods were investigated and proposed an improved SMS (IM-SMS) approach by applying an additional phase shift to help in stimulating the action of the islanding detection, the algorithm keeps the frequency of the converter output voltage deviating until the frequency protection relay is triggered when the utility grid is disconnected.

In [17], a novel anti-islanding method was presented and it enables islanding detection by using the current command with a phase difference. The proposed method cannot only reduce the non-detection zone (NDZ) but also minimize power quality deterioration. Similarly, [18] proposed a method that relies on analyzing the reactive power versus frequency (Q−f) characteristic of the DG and the islanded load. The algorithm is based on equipping the DG interface with a Q−f droop curve that forces the DG to lose its stable operation once an islanding condition occurs. The literature review demonstrates that active schemes can overcome the passive technique's drawback by producing a modest NDZ. Additionally, the active detection methods are more reliable than the passive schemes. However, the primary constraint of the active techniques is the disturbance in the system, which amplifies power quality issues. One percent of perturbance to DG capacity is introduced which cannot degrade the power quality [19]. In term of Dc distribution systems, the active method can be utilized to detect the islanding mode, Active approaches have a longer detection time due to the longer time necessary for the system to respond to the perturbation. Thus, to overcome the limitations of conventional passive and active island detection approaches, some researchers have combined them to produce a more effective hybrid island detection technique. Table 2.3 summarizes the active islanding techniques.

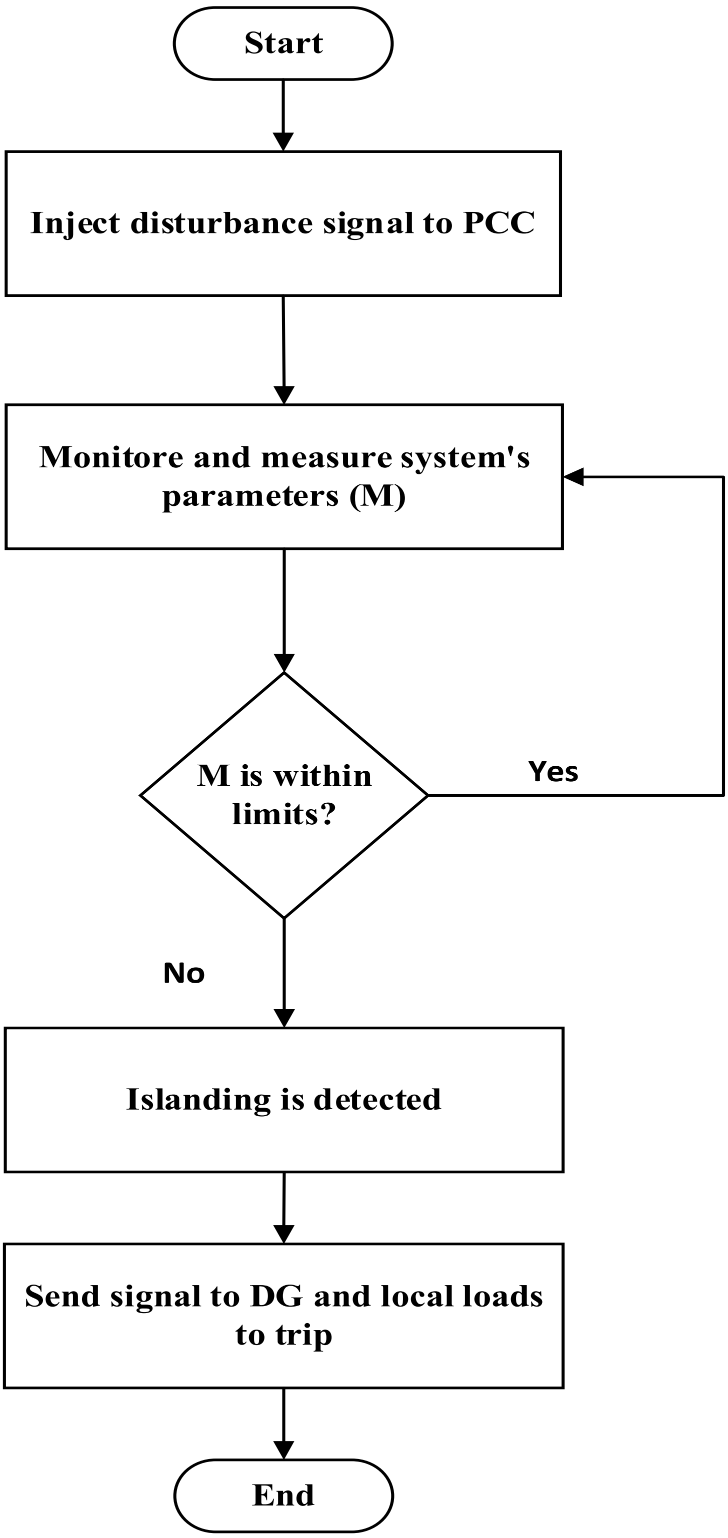


Figure 2.5: Working principle of active islanding detection techniques

Table 2.3: Summary of active islanding techniques

Methods	Advantages	Disadvantages	Effectiveness in Multiply Inverter Cases
Impedance Measurement	Small NDZ for single system. Simple implementation and fast detection.	Produce harmonics. Large NDZ with a large value of Q.	Not effective.
SMS	Low error detection rate.	Problem on system transient stability. Ineffective under a certain load, e.g., RLC resonant load. Large NDZ with a large value of Q.	High effective.
AFD	Simple implementation.	Large nondetection zone with high Q.	Not effective.
SFS	Relatively fast detection. Smallest NDZ.	Difficult implementation, Problem in power quality, system stability	
SVS	Fast detection. Small NDZ.	Increased harmonic distortion.	

2.2.3 Hybrid Techniques

Active and passive detection techniques are combined in hybrid techniques. Active procedures are used only after passive techniques have detected islanding. Figure 2.6 illustrates the detection procedure for hybrid techniques. Some research was developed using this technique. For instance, [26] proposed a hybrid method based on positive feedback and the VU/THD techniques. In [27] proposed a method based on voltage fluctuation injection using a high impedance load which involves two stages, the first of which is the rate of change of frequency (ROCOF)/rate of change of voltage (ROCOV), and the second of which is the correlation factor (CF), to achieve greater efficacy and [28] presented a new hybrid islanding detection technique based on the combination of optimized Sandia Frequency Shift (SFS) method and Rate of Change of Frequency (ROCOF) relay in which the NDZ is decreased and improved the speed of response in comparison with SFS. Meanwhile [29] proposed algorithm requires injection of a low frequency sinusoidal disturbance signal (around 10-20 Hz) into the d-axis current control loop of the Distributed Generators (DGs). Thereafter, it utilizes two different features obtained from the superimposed component of d-axis voltage sensed at the point of common coupling (PCC) of the DGs for detecting unintentional islanding events. Another hybrid method was proposed by [30] based on frequency shift and root mean square of voltage due to voltage interpolation of Fourier transform when Gibbs phenomenon occurs.

Another method proposed by [31] that combines voltage unbalance and total harmonic distortion (VU/THD) detection and bilateral reactive power variation (BRPV). The approach modified the conventional VU/THD method to realize fast and accurate detection, and the threshold setting principle is analyzed for the first time based on an equivalent circuit approach. The BRPV method is only triggered when the islanding condition is suspected by VU/THD method. By doing so, the islanding detection performance can be improved significantly without reducing the power quality. The literature review demonstrates that hybrid schemes can overcome the passive and active technique's drawback, bus it was clear that these methods still degrade the power quality and affect the system stability. So, another field of research was explored by researchers which focus on using signal processing and intelligent methods to limit the previous challenges. Table 2.4 summarizes some of the hybrid islanding techniques.

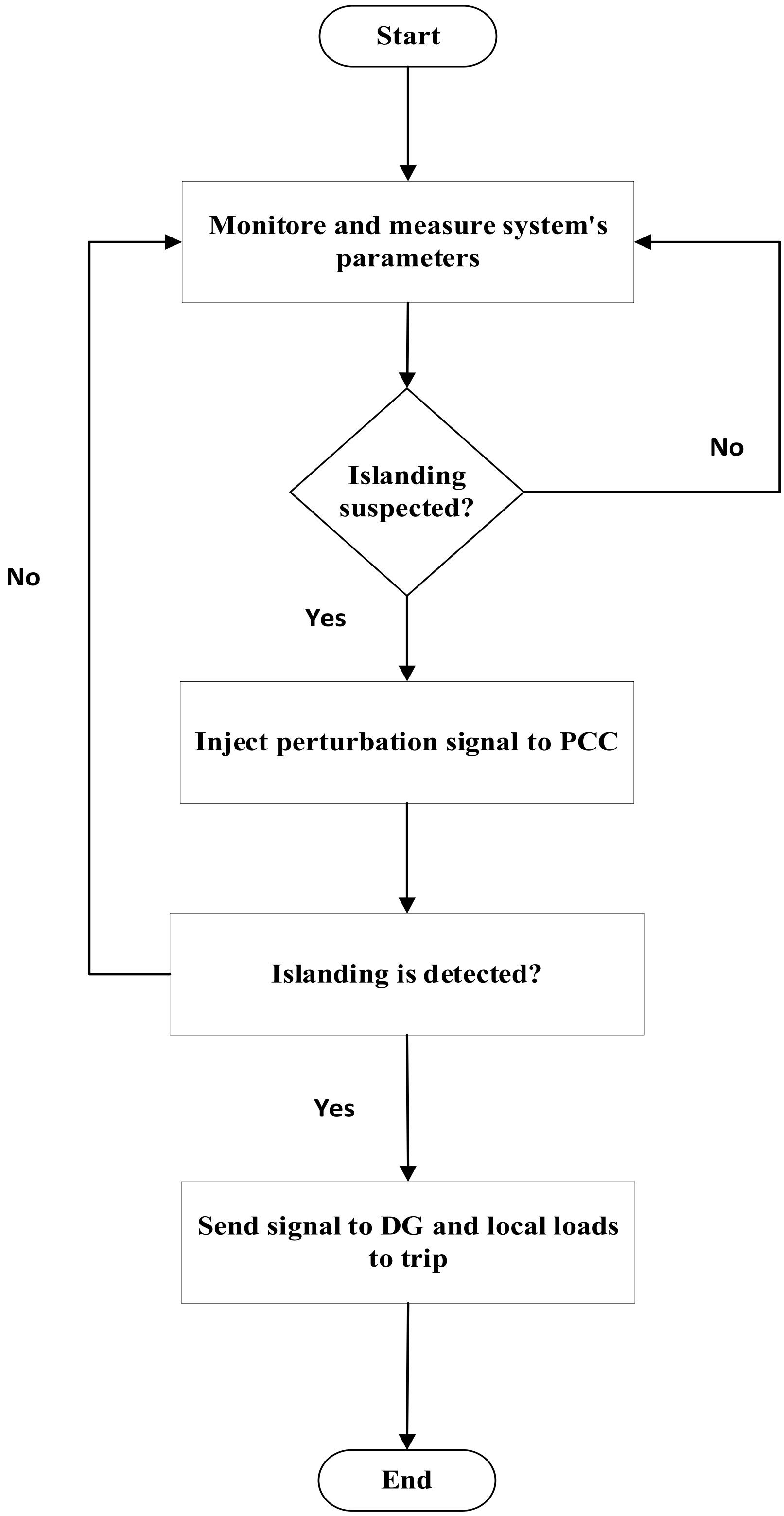


Figure 2.6: Working principle of hybrid islanding detection techniques

Table 2.4: Summary of hybrid islanding techniques

Methods	Advantages	Disadvantages	Effectiveness in Multiply Inverter Cases
ROCOV and Power Variation	Small NDZ. Low error detection rate.	Hard implementation. Slightly degrade power quality.	
VU and SFS, SVS	Very small NDZ.	Degrade power quality.	Effective.
ROCOF and IM	Small NDZ.	Slow detection.	Not effective.
VU/THD and BRPV	Fast detection.	Degrade power quality.	Effective.

2.3 Feature Extraction Schemes

Extracting the most distinctive features from a signal is the most crucial step in preparing input for an intelligent classifier. The feature extraction process is generally implemented by using signal processing techniques that are frequently applied to enhance the efficacy of passive islanding detection schemes. The signal processing techniques' versatility, stability, cost-effectiveness, and ease of modification enable researchers to extract the hidden characteristics of observed signals for islanding detection.

The island mode must be detected as fast and precisely as feasible. As a result, researchers are actively investigating intelligent approaches for detecting and characterizing the status of islanding. Based on these extracted features, a determination can be made regarding the occurrence of islanding. The detection process of the signal processing method is depicted in Figure 2.7. Signal processing techniques exhibit a variety of characteristics, such as the time-frequency distribution (TFD) of a time series, which facilitates signal interpretation and quantification regardless of the classification approach used. The linear TFD techniques were commonly implemented in determining the islanding condition because such implementation is faster than those of nonlinear methods [9]. Fourier transform (FT), S-transform (ST), Hilbert Huang transform (HHT), wavelet transform (WT), tt-transform, autocorrelation function-based, and Kalman filter-based are the main signal processing tools utilized for islanding detection. The next sections describe the signal processing methods used in islanding detection strategies.

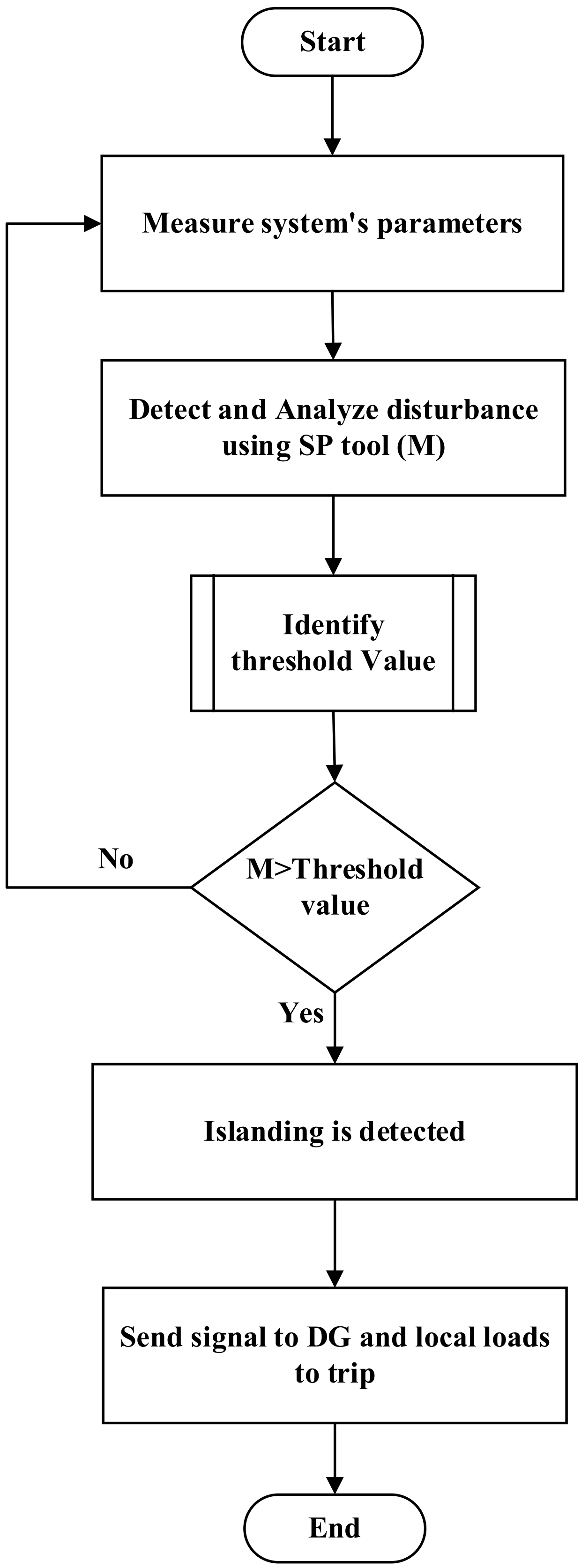


Figure 2.7: Working principle of signal processing islanding detection techniques

2.3.1 Fourier Transform (FT)

Signals can be expanded as a summation of sinusoidal components with varying frequencies. The Fourier transform extracts the features of a stationary signal at specified frequencies. The Discrete Fourier Transform and the Short Time Fourier Transform are two variants of the standard Fourier Transform used to detect islanding mode. For instance, [32] proposed a new passive island detection technique based on DFT for obtaining the desired features. The suggested approach involves the use of variations in the grid voltage's second harmonic component. It takes advantage of the fact that harmonic coefficients vary according to normal and islanding conditions. The utilization of harmonic coefficients provides effective protection against grid disruptions and helps minimize the NDZ. The detection time for islanding is around 1 millisecond (ms) due to the use of a high-performance DSP controller.

To address the issue of DFT's slow or reduced computing time, the Goertzel algorithm is applied in [33], which is a discrete Fourier transform, and it is the fastest way to figure out the pitch of identification. It directly calculates the amplitude and phase of the input signal's target frequency, which significantly decreases the computational time. The Goertzel algorithm was used to reduce the islanding detection time in a single-phase, two-stage photovoltaic (PV) system. In the proposed system, the inverter injects the output current with a ninth harmonic component into the grid and detects the same in voltage at the point of common coupling. NDZ does not exist in this method, even under perfect power mismatch. The impact on the quality of the power is also very small, and islanding is detected in two cycles.

2.3.2 Wavelet Transform (WT)

The wavelet transform (WT) can be described as a mathematical model built on the foundations of the square integral. The wavelet transform is categorized into continuous (CWT) and discrete wavelet transforms (DWT), which are used in islanding detection. For instance, in [29], CWT is used in islanding detection by analyzing DG voltage. The Mallat decomposition was utilized to extract and eliminate noise from the signal. By incorporating several coefficients, this strategy reduces computational efficiency.

In [35], a wavelet-based hybrid system (WB-HIDS) was presented for detecting islanding conditions in ac microgrids. A modified CWT algorithm was introduced for accomplishing its real-time implementation (RT-CWT), which improves the non-stationary signal analysis for generating power quality-related indices. In [36], [37], the time localization of signals from a single-phase photovoltaic system was determined using the DWT method. The suggested approach detects islanding by utilizing bi-orthogonal 1.5 and 5 decomposition levels. The decrease in the number of sensors, the reduction of the computational burden, and the reduction of complexity are just a few of the advantages related to this technique. In a related work, [38] presented a DWT-based method for monitoring voltage and frequency fluctuations based on the Daubechies wavelet. The method's distinguishing characteristics include its simplicity of programming, enhanced capabilities for islanding detection, and simultaneous observation of power quality profiles. The strategy can provide the proposed method with practicality, adaptability, and robustness when tested in a variety of scenarios. In [39], a Daubechies db4-based DWT algorithm was proposed and was applied to negative sequence voltage and current signals to detect the islanding mode. The coefficients of change in energy and standard deviations were then utilized as features to discriminate between islanding and non-islanding events. In this technique. Islanding can be easily detected using the first level wavelet coefficients (d1) of the energy and standard deviations in one-cycle signal data. In [40] a Daubechies db4-based DWT was similarly proposed to reduce the NDZ to zero. Researchers benefit from Daubechies db4, which uses spectral changes in higher-frequency components because of its compact and localization properties. Second-level wavelet coefficients (d2) are more robust and less influenced by noise. When compared to the current passive (over/under voltage and frequency) technique, the suggested technique is deemed highly effective in all working situations. One of DWT's drawbacks is the merging of frequencies, particularly at high frequencies. As a result, in [41], the "Haar" mother wavelet, was utilized after measuring the terminal current of DG as a parameter. This type of mother wavelet requires the fewest levels of decomposition and thus has the shortest detection time.

It was proposed a new index called the node rate of change of power index [42]. This index was used to quantify the change in power at each WPT sub-band. The Daubechies db10 served as the basis of WPT, which had a smaller number of wavelet coefficients without affecting the accuracy of the results. It was proposed voltage profiles were analyzed by db5-based DWT to detect the islanding mode of wind turbines [43]. The proposed scheme proved reliable under different load conditions and detected islanding events successfully in both experimental and simulated systems. To overcome the drawbacks in WT signal processing techniques, it was proposed a complex DWT method along with the FPGA implementation using a direct form of FIR filter which can identify the status of the electrical grid [44]. This can easily identify the variations in PCC voltage and determine whether there is an islanding event or not, even in a zero-power mismatch condition, while maintaining no non-detection zone and good power quality. Also, It was proposed the entropy of DWT is used to enhance the proposed approach of islanding detection owing to transient disturbances in the power system [45].

2.3.3 Stockwell Transform (ST)

The time-frequency representation of the wavelet transforms (WT) extracts the desired signal features. The main challenge of WT is its inability to detect islanding mode in noisy environments. As a result, the S-Transform was developed as a modification to WT. The real and imaginary spectra can be located using the frequency-dependent resolution of ST, which provides multiresolution. Meanwhile, the absolute phase of each frequency component stays the same, which makes it a good tool for detecting disturbances in noisy places. For instance, in [46], [47], the negative sequence voltage signal is analyzed through wavelet transform and S-transform for islanding detection. The proposed method was also used to study the voltage profile at the point of PCC with a non-linear load connected. Islanding events were also detected using performance indices such as the energy content and standard deviation of the transformed signal. The results demonstrate the superiority of the S-transform over the wavelet transform for detecting and localizing islanding events.

Towards the same objective, it was proposed an approach based on the s-transform [48]. A cumulative sum detector (CUSUM) was derived based on the spectral energy content of the negative sequence component of the current and voltage signals. The technique was proven to be extremely effective at detecting islanding in a wide range of power distribution network operating situations, including those with several DGs. Because the computational burden of ST is relatively large, it disappoints when used for real-time protection. An advanced version of ST called Sparse S Transform (SST) was proposed by [49],

The SST method gives a faster response than the ST methodology by excluding extraneous data and collecting the signal's essential information to produce the ST matrix. Thus, by reducing processing complexity, the SST technique significantly reduces the computational burden and memory requirements; hence, it is more suitable for real-time implementation. For islanding cases under closely matched power scenarios and the simultaneous occurrence of islanding events with power quality disturbances, the method clearly distinguishes the non-islanding disturbances from islanding events and hence avoids misdetection. The signal processing approaches used in islanding detection are summarized in Table 2.5.

Table 2.5: Summarization of signal processing islanding techniques

Category	References	SP Method	Tested DG System	Time of Detection	Advantage and Disadvantage
FT	Kim et al. [32]	DFT	PV	Around 1 ms	Robust control against grid disturbance
	Kim et al. [33]	DFT (Goertzel Algorithm)	Single phase 2 stage PV PCS	within 2 cycles	Fast harmonic computation
WT	Yanping et al. [34]	CWT	Grid connected DG	0.6 s	Low computational efficiency
	Paiva et al. [35]	RT-CWT	Hybrid (PV, Wind, Hydro)	Around 2 s	Robust control against grid disturbance
	Pigazo et al. [36], [37]	DWT	Low voltage and low power PV ystem	Less than 30 cycles	Minimum computational burden
	Hsieh et al. [38]	DWT	DG installed on petroleum company	less than 0.1 s	Highly effecient
	Samantara et al. [39]	DWT	Wind farm (DFIG)	1 cycle	Highly effective
	Dwivedi et al. [40]	DWT	Grid connected PV system	2.5 power frequency cycles	Highly efficient and diminishes NDZ
	Shariatinasab & Akbari [41]	DWT	Third decompositionlevel	1/3 of cycles	
	Karegar et al. [43]	DWT	IG type wind turbine	< 0.2 s	More reliable
	Buduma et al. [44]	DWT	Single DG PV system		
	Azzaoui et al. [45]	DWT	Islanding test scheme, as specified by IEEE 1547-2018 and IEEE 929-2000 standards	Within 20 ms	reliable and robust under transient disturbances
	Morsi et al. [42]	WPT	Wind farm (9 MW)	0.06 s	Simplicity, computationally efficient implementation with high accuracy
ST	Ray et al. [46], [47]	S-transform	Inverter based & rotating machine based i.e. PV, Fuel cell and wind	26–28 ms	Efficient under noisy environment
	Mishra et al. [49]	S-transform	PV System	17-29 ms	Less computational burden

2.4 Intelligent Classifiers for Islanding Detection

The desired features of the input signal should be extracted and compared to a threshold value. Choosing a threshold value is a difficult task. If the threshold value is set too high, the islanding event will not be detected; conversely, if the threshold value is set too low, the DG will trip even in the presence of disturbances, resulting in a false detection. To address this issue, a proper tool is required to attain both great sensitivity and accuracy.

Combining intelligent classifiers and signal processing tools demonstrates that this goal might well be accomplished in the case of islanding detection. Intelligent classifiers which commonly used in signal processing-based islanding detection techniques are artificial neural network (ANN), probabilistic neural network (PNN), decision tree (DT), adaptive neuro-fuzzy inference system (ANFIS), random forest (RF), support vector machine (SVM) and Fuzzy logic control. Figure 2.8 illustrates the process needed in classifying islanding conditions. The following sections describe some of the intelligent classifier methods used in islanding detection.

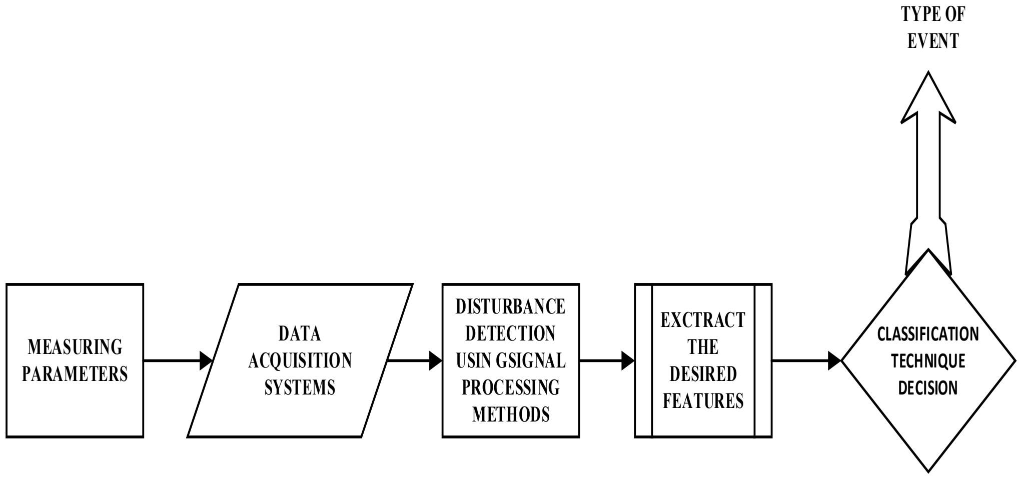


Figure 2.8: Working principle of intelligent classifier-based IDS

2.4.1 Use of ANN as Classifier for Islanding Detection

The fundamental element of ANN is the collection of processing blocks commonly known as nodes or neurons. It can also be interpreted as a directed graph in which a transfer function is executed on each node [50]. The term "training" or "learning" refers to the process of adjusting weights using an effective method. It is possible to detect any changes in the data using this model, which has a wide range of intriguing and appealing properties. Consequently, the model is widely employed in several fields, including islanding detection. For instance, [51] proposed an ANN based method for islanding detection of distributed synchronous generators. The islanding condition can be detected based on samples of the voltage waveform measured at the distributed generator terminals only, which is an important advantage over other ANN-based anti-islanding methods. A data selection process has been presented to generate a training data set for the ANN, which allows the ANN to be trained more effectively, so the proposed technique is robust to erroneous operations. This ANN presented 99.88% of successful results for a detection time of 2 s, 94.71% of success for 1 s, and 92.91% for 0.5 s, even considering the most difficult operating conditions to detect islanding situations. Meanwhile [52] suggested an intelligent islanding detection technique based on an ANN that utilizes only a few features from the power system. Using evolutionary programming (EP) and particle swarm optimization (PSO), the trained ANN's accuracy is increased by adjusting the learning rate, momentum, and number of neurons in the hidden layers.

To determine the optimal feature combination for efficient islanding detection, stand-alone ANN, ANN-EP, and ANN-PSO performance is compared in the form of regression values. A novel detection method proposed by [53] for islanding events in

DG systems based on feature extraction, DWT, and ANN. The suggested approach requires the rate of change of frequency at the DG's terminal and then extracts the desired features from DWT. These features are then used as input to an ANN. [54] proposed a new islanding detection technique based on tunable Q-factor wavelet transform and an ANN for photovoltaic-based distributed power generation (PV-DPG). Using an ANN classifier, PV-DPG states were classified as non-islanding or islanding with 98 percent accuracy. Additionally, the results demonstrating the proposed approach's efficacy in noisy and non-noisy conditions were discussed. In [55] the detection approach was proposed using the frequency spectrum of the voltage at the DG's terminals. The S-transform was used to produce the frequency spectrum then an ANN classifier was used. The suggested approach outperformed existing methods in terms of accuracy and detection time, with an average detection time of 26 ms.

Besides the main application of ANN, Grey Wolf optimized artificial neural network (GWO-ANN), probabilistic neural network (PNN), extended neural network (ENN), back-propagation neural network (BPNN), self-organizing map (SOM), and modular probabilistic neural network (MPNN) are some ANN variants that have found application in islanding detection. In [56] the suggested method was based on an intelligent islanding detection method (IIDM) based on a grey wolf optimized intrinsic mode function (IMF) feature-based grey wolf optimized artificial neural network (GWO-ANN). To obtain highly involved features in the proposed IIDM, the modal voltage signal was pre-processed using variational mode decomposition followed by a Hilbert transform on each IMF. The energy and standard deviation of IMFs were then used to train and test the GWO-NN model for differentiating between islanding and non-islanding events. In the presence of noise in the test signal, the proposed IIDM was able to distinguish between islanding and non-islanding events without demonstrating any sensitivity. Aziah in [57] proposed a simple and effective passive islanding detection approach combined with a PNN Classifier. The features were extracted from the DG's three-phase voltage by using the phase space technique. Using this approach, many hidden features were discovered from the original signal, which was then fed into the PNN classifier. The proposed detection method provided 100% accuracy. The combination of a wavelet packet transform (WPT) and a probabilistic neural network (PNN) for grid-tied photovoltaic systems was proposed in [52]. The (PCC) voltage was recorded and processed using the WPT to determine the normalized Shannon entropy (NSE) and the normalized logarithmic energy entropy (NLEE), after which the events were classified using a PNN classifier. By utilizing the desired features, the suggested method didn't not mal-operate during islanding and non-islanding events. Furthermore, it is more accurate than other smart and passive approaches because of its simplicity, specificity, and lower costs.

Another scheme based on the combination of Slantlet Transform (SLT) and PNN for Grid-Tied Photovoltaic systems was proposed in [54]. The SLT was used to extract the unique feature vector from three-phase voltage signals at the PCC to feed the PNN classifier. The proposed technique was compared with the ROCOF relay. The efficiency of the proposed method was exposed by the results to distinguish between islanding cases.

2.4.2 Use of DT as Classifier for Islanding Detection

Another classification method is the decision tree (DT) which is the most widely used tool as an intelligent classifier [55]. In the study of [61], an intelligent islanding algorithm based on multivariate analysis and data mining techniques was developed.

The proposed method produces decision trees that establish the tripping logic, protection handles, and thresholds for each DG-islanding relay in the distribution network. The intelligent islanding relay (IIR) developed using the suggested approach has consistently high-level performance in terms of dependability and security and includes reduced NDZ compared to the islanding devices currently in use.

It was proposed that a hybrid islanding detection method based on DT and Sandia frequency shift (SFS) for grid-connected inverter-based DGs was proposed [62]. Under various power mismatch circumstances, power quality events, and the existence of single or multiple grid-connected inverter-based DG units, detailed case study findings confirmed the effectiveness of the suggested strategy. Meanwhile for the detection of islanding events in hybrid distributed generation systems with inverter and synchronous machine-based distributed energy resources. In a related work, [63] suggested an algorithm based on the decision tree (DT) learning method with hardware-in-the-loop (HIL) simulations. DT was utilized to differentiate between islanding and non-islanding events. In addition to a significant reduction in NDZ, the proposed intelligent islanding relay (IIR) offered high levels of dependability and security. Similarly, [64] proposed an intelligent relay based on a DT classifier. The proposed scheme utilized the NDZ boundaries of the existing standard relays and applied a comprehensive training or testing strategy that effectively reduced the NDZ by over 54% compared to the standard relay function.

As an islanding detection technique, the FL methodology can also be used as a classification method. An islanding detection approach based on hybrid fuzzy positive feedback (PF) was proposed in [65]. Design considerations for frequency and voltage inputs were included in the fuzzy inference principles to develop this system. The simulation and experimental data were presented to demonstrate the success of the proposed methodology, which decreased the detection time by 77.3 % in comparison to the classical method. In [66], a new hybrid islanding detection approach was proposed for multi-connection point smart grid models that focused on the probability of islanding (PoI) in these systems. Active, passive, and communication-based islanding schemes were used to measure the PoI at various locations, and the results were transmitted to the central MG control. The voltage and current measurements were processed using the DWT to extract the features and then fed into fuzzy neural networks to detect islanding.

2.4.3 Use of other IC for Islanding Detection

Other classifiers also were used in the islanding detection issue. For instance, support vector machine (SVM), was used in the proposed method in [67]. For the final SVM algorithm, seven features were employed to detect islanding and faults as training and testing polygons to produce the results more efficiently. Reference [68] proposed a new islanding detection strategy for low-voltage (LV) inverter-interfaced microgrids based on an adaptive neuro-fuzzy inference system (ANFIS). Seven features at the PCC were measured and monitored by the ANFIS classifier. The effectiveness, authenticity, selectivity, accuracy, and precision of the suggested method were demonstrated by MATLAB/Simulink simulations and a variety of tests involving different active load situations and several DGs. Table 2.6 highlights some of the benchmark studies that utilized AI-based islanding detection techniques.

Table 2.6: Summary of AI classifier-based IDS

References	Feature extraction	Classification	Recognition Rate %
Merlin et al. [51]	Passive	ANN	99.88
Raza et al. [52]	Passive	ANN	99.6
Hashemi & Mohammadi [53]	DWT	ANN	100
Menezes et al. [55]	ST	ANN	100
Kumar et al. [54]	TQWT	ANN	98
Admasie et al. [56]	IMF	ANN	88.9
Khamis et al. [57]	WT	PNN	95.0
Ahmadipour et al. [58]	DWT	PNN	98.00
Masoud et al. [59]	DWT	PNN	94.0
Li et al. [61]	passive	DT	100
Azim et al. [62]	passive	DT	100
Chandak et al. [64]	passive	DT	100
Aguiar et al. [65]	Active	FL	>96
Kermany et al. [66]	DWT	FL	-
Baghaee et al. [67]	passive	SVM	100
Mlakic et al. [68]	Passive	ANFIS	-

2.5 Chapter Summary

This chapter provides an overview of several islanding detection methods, as well as the benefits and drawbacks of the most used islanding detection and classification strategies. A review of the most recent islanding detection approaches, such as feature extraction and intelligent techniques, is also provided and discussed. According to the literature, the most effective scheme for islanding detection is the signal processing based methods with AI application. However, more research is needed to improve this technique so that islanding can be detected as soon as possible within 2 seconds. Therefore, the aforementioned challenges are addressed by developing an alternative islanding detection technique discussed in Chapter 3.

Chapter 3: Islanding Detection Using GT and ANN

3.1 Introduction

Unintentional islanding can have detrimental impacts on the system and its components, so events that may indicate this must be detected as fast as feasible. The most accurate method for detecting islanding events in a system is to use SP with intelligent approaches like ANN. The application of SP approaches in islanding detection, such as DWT enables the extraction of unique features of measured signals to differentiate the islanding state, which is then utilized as an input for the intelligent classifier.

This chapter explains the design of the proposed islanding detection methodology for a radial distribution system with DGs, which uses the GT as a feature extraction method. These parameters are fed into the neural network classifier, specifically the Categorical Gradient Boosting (CatBoost) Classifier. Based on the three-phase voltage signal and instantaneous power measurements per phase at the DG terminals, the proposed islanding detection technique identifies islanding and non-islanding events such as faults, capacitors, and load switching. GT method mentioned in Section 3.3 is used to extract the features of such occurrences. Sections 3.4 outlines the methods used to assess the accuracy and effectiveness of the proposed strategy, and a summary of this chapter is drawn in Section 3.5.

3.2 Tools and Methods used in the Proposed Method

This section provides an overview of the main tools and methodologies used in constructing the suggested islanding detection approach, particularly the GT method and CatBoosT. The suggested method's initial stage involves feature extraction. As a result, Section 3.2.1 describes the primary notion underlying the Gabor transform SP technique and Section 3.2.2 summarizes the main ideas about the IP theory and some information about the IP per phase. Meanwhile, Section 3.2.3, Section 3.2.4, and Section 3.2.5 provide an overview of the CatBoosT, ANN, and RF classifier's essential processes. Respectively

3.2.1 Gabor Transform (GT)

GT is an extended version of short time Fourier transform (STFT) which is one of many time-frequency analysis methods commonly employed to study non-stationary signals. When comparing the STFT to the FT, the most important difference is the employment of windows function w(s). When the windows function is moved on the time axis and spectrogram of FT, time-frequency analysis can be viewed. The STFT is defined as:

$$STFT(t,\omega) = \int_{-\infty}^{\infty} w(\tau) f(\tau + t)\, e^{-j\omega\tau} d\tau \qquad \text{Equation (1)}$$

where t is a sliding variable of time, ω is the angular frequency, τ is the signal function in the time-domain and $\mathrm{w}(\tau)$ is the window function. The GT can be seen as a type of STFT, which replaces the window function with Gaussian function as shown below [69].

$$GT(t,\omega) = \int_{-\infty}^{\infty} g(\tau) f(t + \tau)\, e^{-j\omega\tau} d\tau \qquad \text{Equation (2)}$$

Where $g(\tau)$ is Gaussian function with specific length and can be obtained as below

$$g(\tau) = e^{-\alpha\pi t^2} \qquad \text{Equation (3)}$$

The final definition used for GT is as follows:

$$GT(t,\omega) = \int_{-\infty}^{\infty} e^{-\alpha\pi(\tau-t)^2} f(t+\tau)\, e^{-i\omega\tau} d\tau \qquad \text{Equation (4)}$$

The coefficient α controls the window length. Therefore, it has a direct influence on the time-frequency resolution [70]. From Equation (4) it is easily known that the GT is a special case of STFT using the Gaussian function as a window. The application of the Gaussian window in GT provides the best time-frequency resolution as it holds good energy concentration in the time-frequency domain [71]. The discrete Gabor transform (DGT) is identical to a discrete form of STFT, except that it uses a Gaussian window. For a finite and periodic sequence $x[i]$, it can be expanded as a linear combination of the Gabor coefficients (GC) and basis functions $h_{m,n}[i]$.

$$x[i] = \sum_{m=0}^{M} \sum_{n=0}^{N} C_{m,n} h_{m,n}[i] \qquad \text{Equation (5)}$$

The discrete Gabor coefficients $C_{m,n}$ are obtained as follows:

$$C_{m,n} = \sum_{i=0}^{L-1} x[i]\, \gamma^{*}{}_{m,n}[i] \qquad \text{Equation (6)}$$

where $\gamma[i]$ is a dual basis of $h[i]$ and both form a biorthogonal basis. Finally, the DGT is defined as follows:

$$G_x(m,n) = \sum_{i}^{L-1} x[i]\ \gamma[i - m\Delta M] W_L^{ki} \qquad \text{Equation (7)}$$

where $\gamma[k] = e^{\pi k^2}$, $W_L^{ki} = e^{j(2\pi/L)ki}$, ΔM and ΔN are time and frequency sampling intervals, respectively. M and N are the numbers of sampling in time and frequency domains. L is the number of samples, that is, L-point window [72]. Simulations based on detection algorithms are used to form a comprehensive sample set of all disturbances. This investigation used GT to extract specific features from voltage and instantaneous power per phasr signals to identify islanding and non-islanding occurrences. After that, a CatBoost algorithm which is a gradient boosting method based on decision trees is fed with the corresponding features and then classifies the events.

3.2.2 Instantaneous Power Theory

The theories that deal with instantaneous power can be mainly classified into the following two groups. The first one is developed based on the transformation from the abc phases to three-orthogonal axes, and the other is done directly on the abc phases. The first one is what will be called the p-q theory that is based on the abc to $\alpha\beta 0$ transformation. The second one it deals directly with the abc phases that is, the use of instantaneous phase voltages and instantaneous line currents. The p-q theory is based on a set of instantaneous powers defined in the time domain. No restrictions are imposed on the voltage or current waveforms, and it can be applied to three-phase systems with or without a neutral wire for three-phase generic voltage and current wave forms. The three-phase instantaneous active power $P_{3\phi}$ can be obtained as [73].

$$P_{3\phi} = v_a i_a + v_b i_b + v_c i_c \qquad \text{Equation (8)}$$

Where v_a, v_b and v_c are the instantaneous voltages in the abc phases. Meanwhile i_a, i_b and i_c are the instantaneous current in the abc phases. Each term ($v_a i_a$, $v_b i_b$, $v_c i_c$) separately describes the instantaneous active power per phase which defined as:

$$P_k(\mathrm{t}) = v_k(t) i_k(t) \qquad \text{Equation (9)}$$

$$P_k(\mathrm{t}) = V_m I_m sin^2(\omega t)$$

$$sin^2(\omega t) = \frac{1 - cos(2\omega t)}{2}$$

$$P_k(\mathrm{t}) = \frac{V_m I_m}{2}(1 - cos(2\omega t))$$

Where k is the phase number, V_m and I_m are the maximum values of voltage and current, respectively, and ω is the angular frequency in rad/seconds. From equation Equation (9) it is clear that the instantaneous power per phase consists of two terms, one constant part i.e., $\frac{V_m I_m}{2}$ and another a fluctuating part i.e., $\frac{V_m I_m}{2}$ $cos(2\omega t)$. So, the instantaneous active power per phase is exploited to be used in the proposed method.

3.2.3 CatBoost Algorithm

CatBoost is Derived from the terms 'Category' and 'Boosting' that it is based on a gradient boosting algorithm that is widely used in different machine learning problems like recommendation systems, fraud detection, and forecasting. CatBoost is a recently developed open-source machine learning algorithm that is efficient in predicting categorical features that have a discrete set of values called categories that are not necessarily comparable with each other; thus, such features cannot be used in binary decision trees directly [74].

A category is defined mathematically using an input vector, and network classifiers are trained using data with known classification. Other machine learning techniques require pre-processing steps to convert categorical data into numbers, but CatBoost requires only the indices of categorical features. It then automatically performs one-hot encoding to transform the categorical data into numerical data. Moreover, unlike deep learning, CatBoost does not require huge datasets for extensive training. Despite having several hyper-parameters like regularization, learning rate, number of trees, tree depth etc., CatBoost does not require exhaustive hyper parameter tuning which reduces the likelihood of overfitting. CatBoost uses three steps to transform categorical features having number of categories greater than a specified number into numerical features [75].

1. The set of input observations are randomly permuted multiple number of times.
2. The label values are transformed from categorical or floating point to integer values.
3. The categorical features are transformed to numerical features using the formula given in the following equation:

$$Average\ target = \frac{InClassCounter + Prior}{TotalCounter + 1} \qquad \text{Equation (10)}$$

Where $InClassCounter$ represents the number of times the class label is 1 for all those records having the current feature value. $Prior$ is the starting value for the numerator and is defined during initialization of parameters. $TotalCounter$ is the total number of records (up to the previous record) having the same categorical value as that of the current categorical value [75].

Suppose we observe a data with samples H = {({X_j, y_j})} j=1,2,.,.,.m, where $X_j = (x_j^1, x_j^2, \ldots x_j^n)$ is a vector of n features and response feature $y_j \in$ R, which can be binary (i.e yes or no) or encoded as numerical feature (0 or 1). Samples (X_j, y_j) are independently and identically distributed according to some unknown distribution P (.,.). The goal of the learning task is to train a function $H : \mathbb{R}^n \rightarrow \mathbb{R}$, that best solves the given problem (regression, classification, or multiclassification) for any input object and minimizes the expected loss given below

$$\mathcal{L}(H) \coloneqq \mathbb{E}L(y, H(X)) \qquad \text{Equation (11)}$$

where L(.,.) is a smooth loss function and (X, y) is a testing data sampled from the training data H. The procedure for gradient boosting constructs iteratively a sequence of approximations $H^t : \mathbb{R}^m \rightarrow \mathbb{R}$; t = 0, 1,… in a greedy fashion. H^t, H^{t-1} is obtained in an additive process, such that $H^t = H^{t-1} + \alpha g^t$, with a step size α and function $g^t\colon \mathbb{R}^n \rightarrow \mathbb{R}$, which is a base predictor, is selected from a set of functions G in order to reduce or minimize the expected loss defined in Equation (12) :

$$\begin{gathered} g^t = arg\ min_{g \epsilon G} \mathcal{L}(H^{t-1} + g) \\ g^t = arg\ min_{g \epsilon G}\ \mathbb{E}L\ (y,\ H^{t-1}(X) + g(X)) \end{gathered} \qquad \text{Equation (12)}$$

Often, the minimization problem is approached by the Newton method using a second-order approximation of $\mathcal{L}(H^{t-1} + g)$ at H^{t-1} or by taking a (negative) gradient step. Either of these functions is gradient descent [76]. In ordered boosting, the training data points are fixed in a specific order (σ), and rather than generating a single model, CatBoost obtains several models by increasing the number of training instances in each model one by one in the stated order (σ). The ordered boosting procedure is presented as below:

Step 1: Collect data from the simulation or measurements for the input and target (D).

Step 2: Assemble and pre-process the training data (t).

Step 3: Identify (σ) based on random permutations of t.

Step 4: Calculate the residuals (r).

Step 5: Update models with the associated calculated residuals.

3.2.4 Artificial Neural Network (ANN)

Artificial neural network has been inspired from billions of interconnected neurons in the human brain based on a mathematical configuration. ANN is widely used for control, approximation, and classification problems. ANN model is a structure that can be adjusted to produce a mapping from a given set of data to features of them or relationships among the data. The brief descriptions of the fundamentals can be found in [77].

An ANN is a network of neurons analogous to the biological synapse. Generally, ANN consists of a number of layers and nodes. The input data is sent to the output layer through hidden layers. The nodes in successive layers are interconnected by links. The error signals at the output layer are then propagated back to the hidden layer and input layers. The output of any node in the hidden and output layer is related to the input node by an activating function. The minimization process and the weight updating are performed according to a learning algorithm. ANN has several training algorithms for the learning process. However, Levenberg Marquardt Back Propagation (LMBP) is found to be most effective for the training process.

Multi-layer feedforward networks are widely adopted for power system problems. Backpropagation neural networks are multilayered, feedforward neural networks that are widely used. Multi-layer Perceptron (MLP) with Back-Propagation is also regarded as one of the most basic and general approaches for guided training of multilayered neural networks. Backpropagation works by internally modifying the weight values to approximate the non-linear relationship between the input and the output. It can also be generalized for input not included in the training patterns (predictive abilities). Figure 3.1 illustrates the basic ANN structure [78].

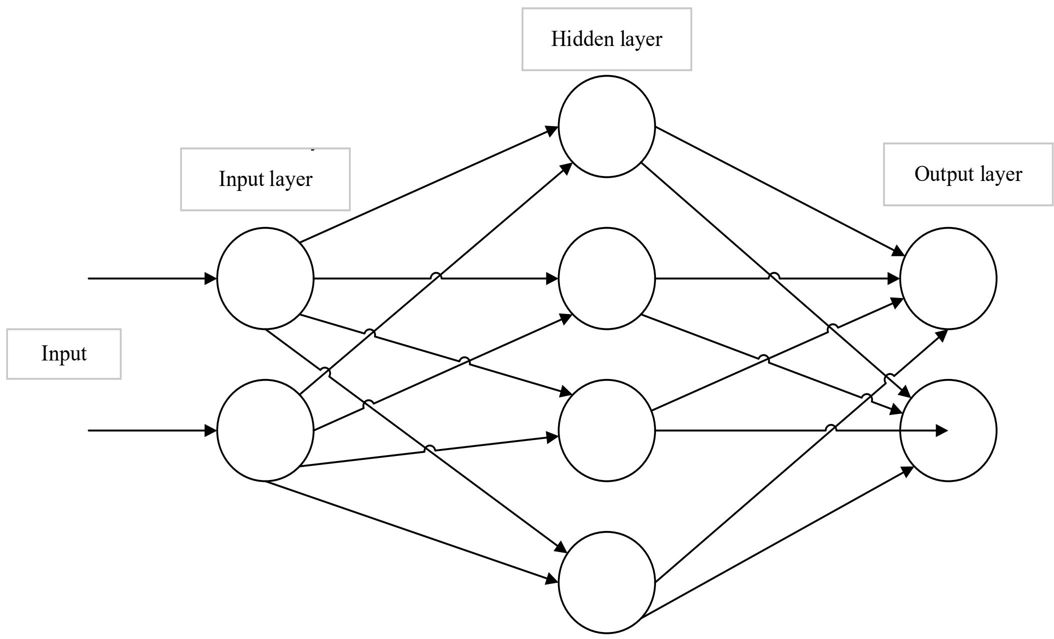


Figure 3.1: Multi-Layer feed forward ANN structure [78]

3.2.5 Random Forest (RF)

The random forest classifier consists of a combination of tree classifiers where each classifier is generated using a random vector sampled independently from the input vector, and each tree casts a unit vote for the most popular class to classify an input vector [79]. An amazing data mining tool, random forest adheres to the principles of supervised learning. Similar to an ANN, it undergoes basic training and testing. Additionally, it is capable of performing classification and regression functions. In an RF classifier, classification trees are the most important building blocks. A classification tree (CT) is also known as a DT because each node has a decision based on binary suggestion and splits on yes-no or true-false type findings. Datasets are essential as input for machine learning techniques. A dataset (DS) can be presented as, $\mathrm{A} = \{(F_1, y_1), (F_2, y_2), \dots \dots . (F_m, y_n)\}, \{F_k = f_{k1}, f_{k2}, f_{k3}, \dots \dots . f_{kp}\}$. That means the dataset contains 'n' number of data, 'm' number of classes and each feature vector has 'p' number of features. Now, a tree construction relies on a threshold value of a particular node in order to make the split decision. Figure 3.2 illustrates an arbitrary example for three classes namely C_1, C_2, C_3. At each node, feature f_i and comparing threshold is so chosen such that it will limit the resulting diversity of the children's nodes. The sub-division of nodes continues until a node appears at the bottom that signifies only a particular class assigned as a prediction to input feature vector F_k. Now a random forest as a collection of decision trees can be mathematically represented as, $\mathrm{RF} = \{T_1(f, y), T_{21}(f, y), \dots \dots . T_{\mathrm{b}}(f, y)\}$.

Further, for a decision tree T_{k}, its parameters can be termed as, $\mathcal{E}_{\varkappa} = (\mathcal{E}_{\varkappa 1}, \mathcal{E}_{\varkappa 2}, \mathcal{E}_{\varkappa 3} \dots . \mathcal{E}_{\varkappa \mathrm{q}})$. These parameters decide many things such as the structure of DT, which variable splits in which node, choosing random subset of dataset for a tree. Elaborately, $\mathcal{E}_{\varkappa}$ randomly chooses $DS\ \mathcal{E}_{\varkappa}$ as a subset of DS along with $f\ \mathcal{E}_{\varkappa}$ as a subset of F to build a DT namely T_{k} of the RF. That means, each DT of the forest will be constructed using a different subset of data and features at random, thus, satisfying its name random forest [80]. Figure 3.3 demonstrates RF inference for a simple classification example with $\mathrm{T_k} = 3$.

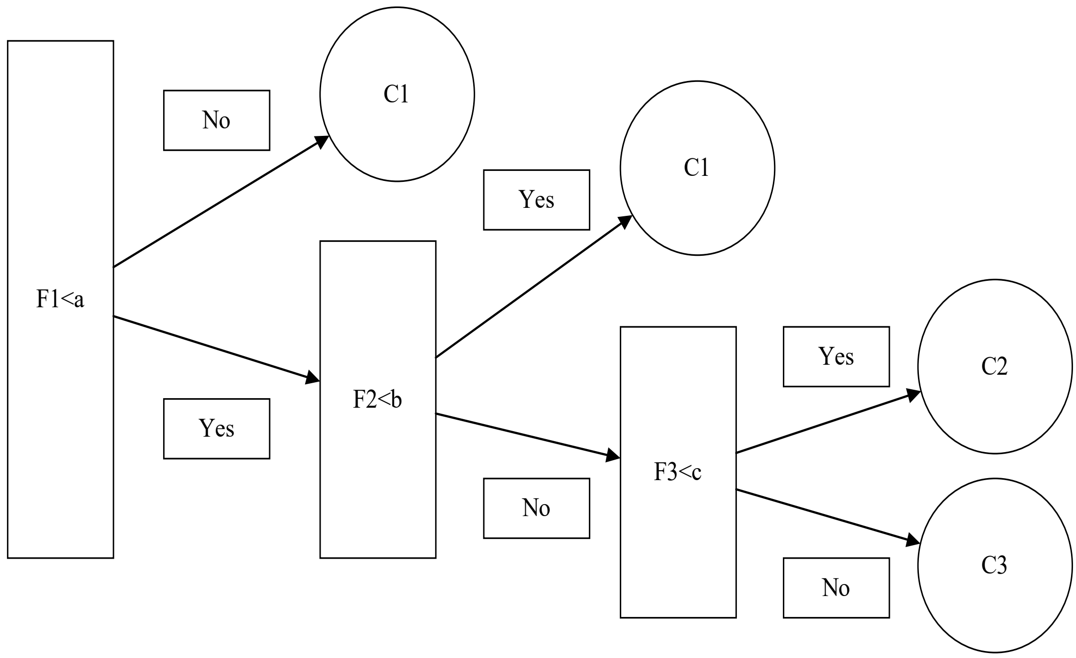


Figure 3.2: An arbitrary DT

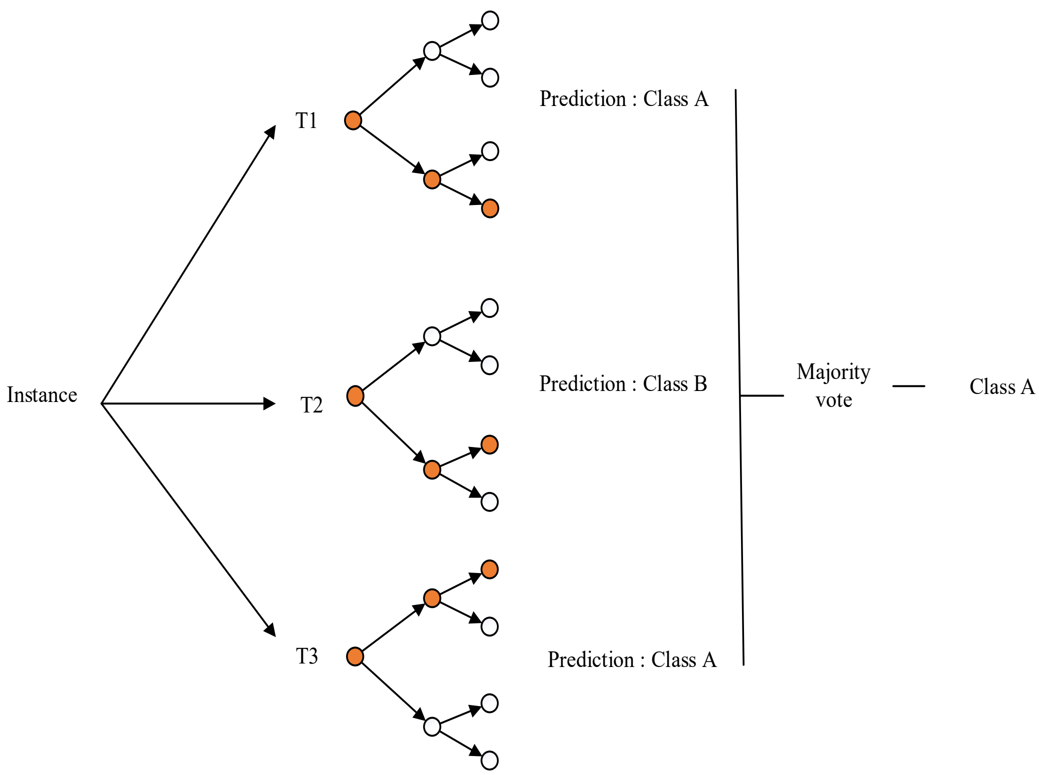


Figure 3.3: RF inference

3.3 Proposed Islanding Detection Scheme

This section covers the proposed islanding detection process in depth. It consists of numerous stages, beginning with data collection, feature extraction, and CatBoost classifier building.

3.3.1 Data Collection

Numerous case studies must be conducted prior to doing the islanding detection feature extraction to produce training data for the CatBoost classifier. The DIgSILENT Power Factory® program is used to simulate a variety of islanding and non-islanding events, including faults, load switching, and capacitor switching. Three-phase voltage and instantaneous power per phase signals are measured at DG terminals during the disturbance from the simulation. The Phase a from the two signals is processed using GT approach to construct feature vectors and then used as input parameters for the CatBoost classifier. Table 3.1 displays the predefined event class parameters based on the type of disturbance.

Table 3.1: Classifier outputs

Event Type	Target
Normal Operation	1
Capacitor Switching	2
Load Switching	3
Tripping events	4
Island Event	5
Line to Line Faults	6
Three-phase Fault at DG2	7
Line to Ground Fault at PCC	8

3.3.2 Gabor Transform Feature Extraction

Extraction of features is critical for creating multiple-parameter-based islanding detection. The suggested Gabor feature aims to identify the unique signature of the voltage and instantaneous power per phase signals, processing these signals using GT extract some crucial variables such as GM and GC which can be used to distinguish islanding events from other events. GC can be found by (6) and after plotting the time-frequency representation of the discreet GT the GC values can be shown clearly. The GC matrix contains the index values of each frequency component at a specific time. For instance, the index value of the fundamental frequency in the normal operation is 17.6055, but in other event will be different. So, five features are extracted from GM and GC. A description of some variables and the selected features are described in Table 3.2 and Table 3.3 respectively.

Table 3.2: Gabor symbols

Symbol	**Description**
D	Index values of GC
R= max (abs (GM))	Maximum values of the absolute value of GM

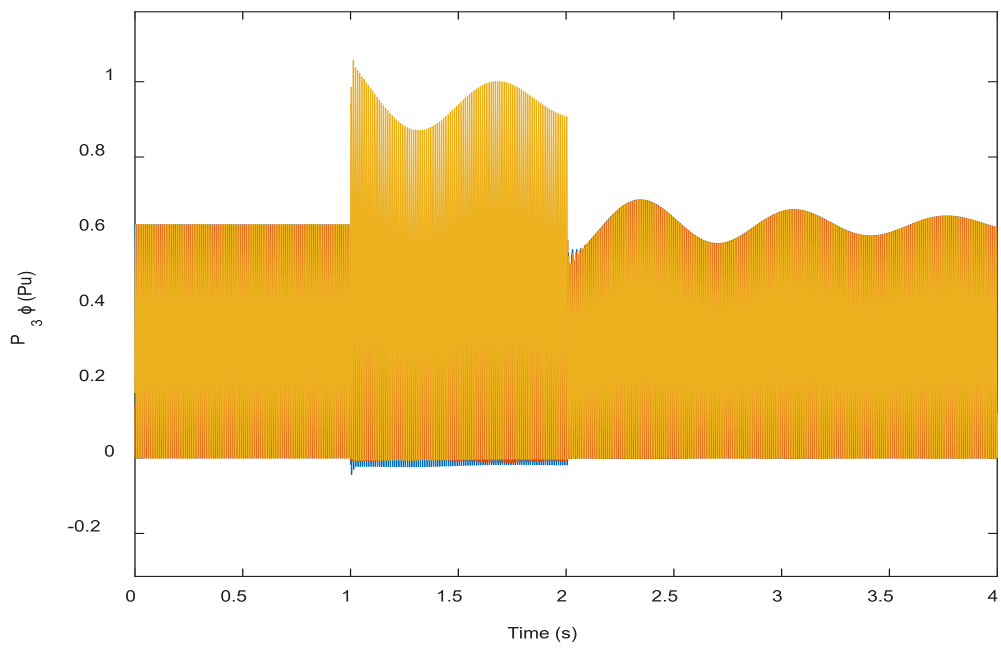
Table 3.3: Selected Gabor features

Feature	**Description**
F1	Minimum of D for the instantaneous power signal during the disturbance
F2	Maximum of D for the instantaneous power signal during the disturbance
F3	Minimum of D for the voltage signal during the disturbance
F4	Maximum of D for the voltage signal during the disturbance
F5	Mean of R for the voltage signal during the disturbance

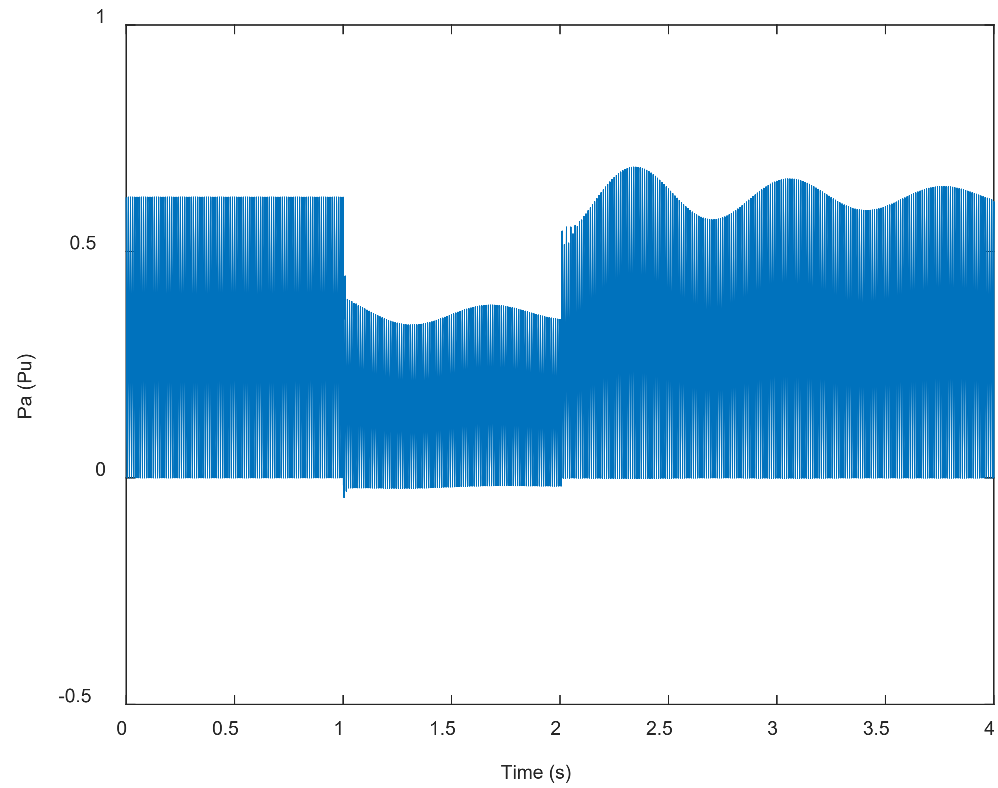
The features with minimum and maximum of D during the disturbance can be obtained at specific period and within certain frequency range. Meanwhile, the features with a mean value of R can be calculated from the equation below:

$$\bar{E} = \frac{\sum_{x=1}^{n} E_x}{n} \qquad \text{Equation (13)}$$

where n is number of the sample points. An example of the IP and voltage waveforms during a single-phase fault at a DG in a distribution system and a representation of the corresponding GT are illustrated in Figure 3.4 and Figure 3.5, respectively. Figure 3.4 (b) demonstrates the IP signal for phase a, which is processed using the GT as illustrated in Figure 3.4 (c). Figure 3.5 (b) shows the voltage signal for phase a, which is also processed using the GT as described in Figure 3.5 (c). Therefore, the values for the minimum and maximum of D can be extracted from Figure 3.4 (c) and Figure 3.5 (c). Meanwhile, the mean value of R can be calculated as depicted in Figure 3.6.

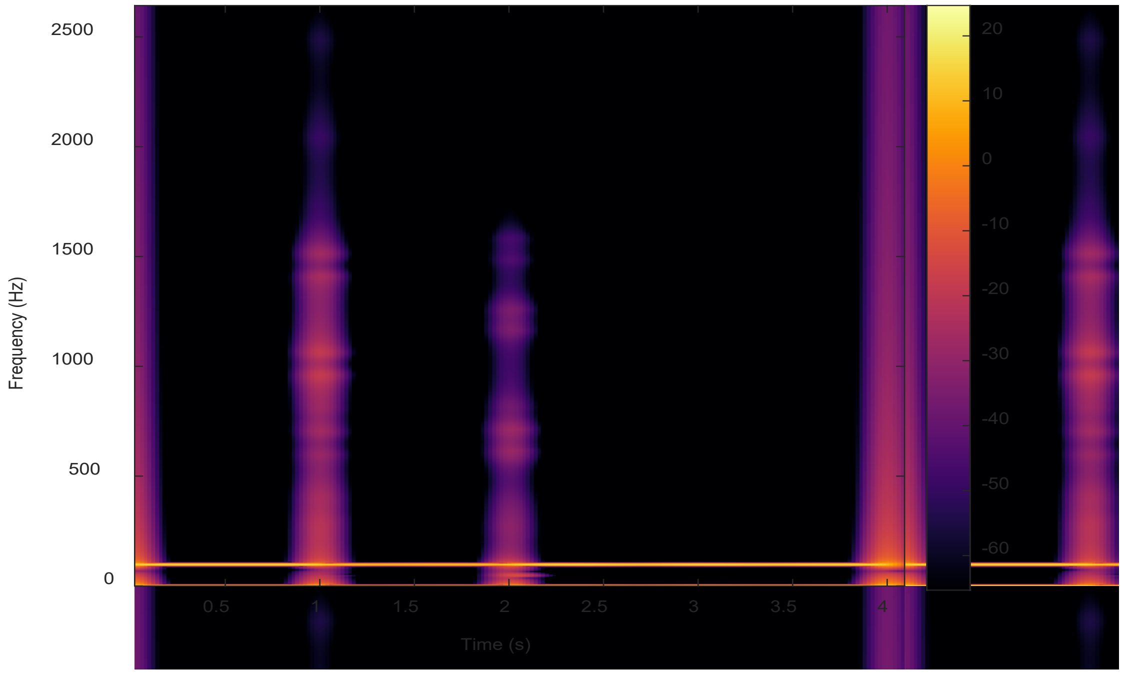


(a)



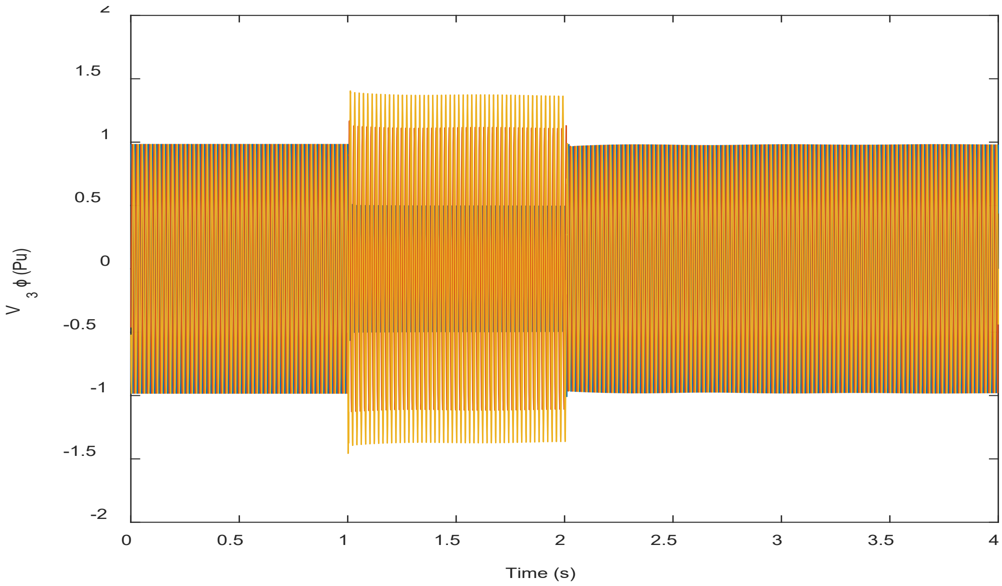
(b)

Figure 3.4: GT feature extraction from IP per phase signal. (a) Three phase instantaneous power per phase signal during single-phase fault. (b) Instantaneous power signal per phase for phase A. (c) Time-frequency representation of GT for Signal (b)



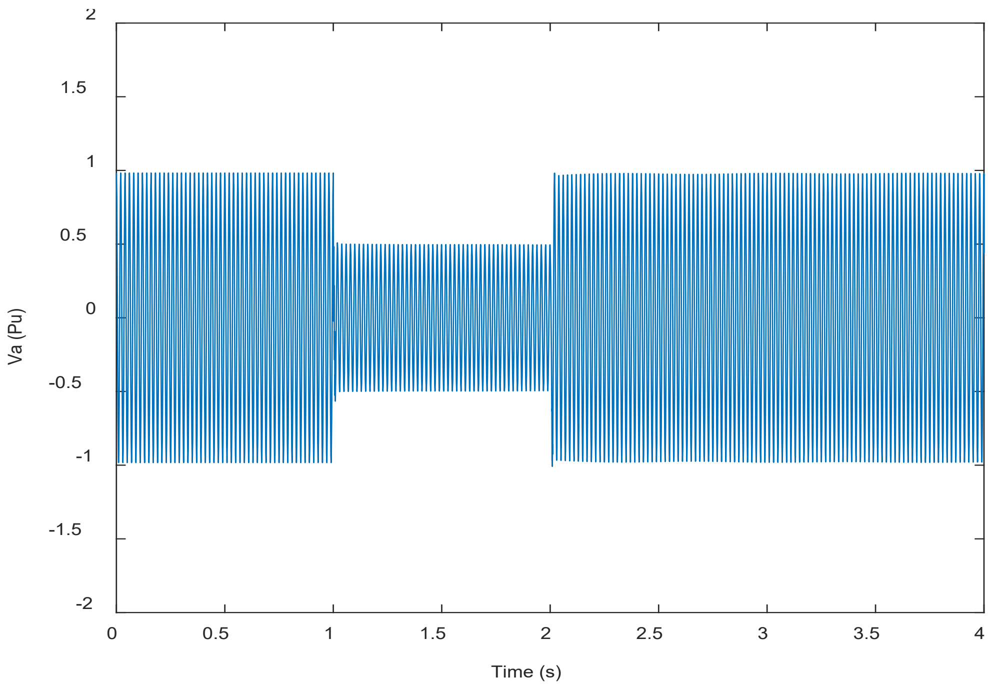
(c)

Figure 3.4: GT feature extraction from IP per phase signal (a) Three phase instantaneous power per phase signal during single-phase fault. (b) Instantaneous power signal per phase for phase A. (c) Time-frequency representation of GT for Signal (b) (continued)

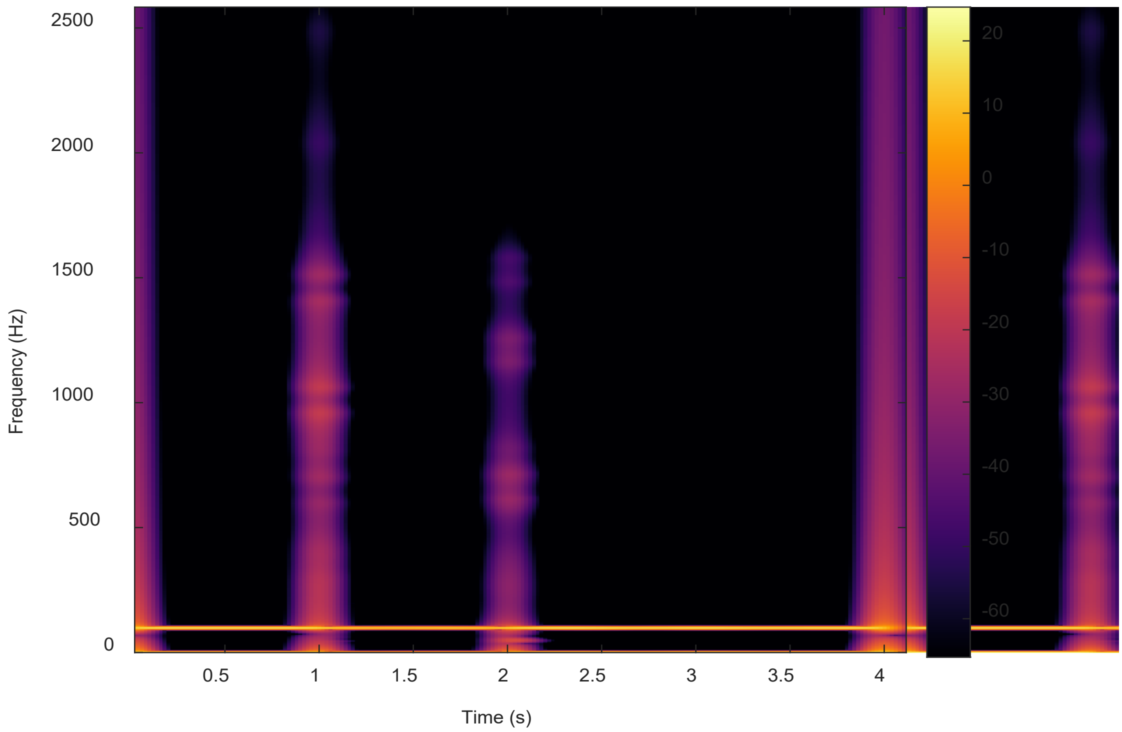


(a)

Figure 3.5: GT feature extraction from voltage signal. (a) Three phase voltage during single-phase fault. (b) Voltage signal for phase A. (c) Time-frequency representation of GT For Signal (b)



(b)



(c)

Figure 3.5: GT feature extraction from voltage signal. (a) Three phase voltage during single-phase fault. (b) Voltage signal for phase A. (c) Time-frequency representation of GT For Signal (b) (continued)

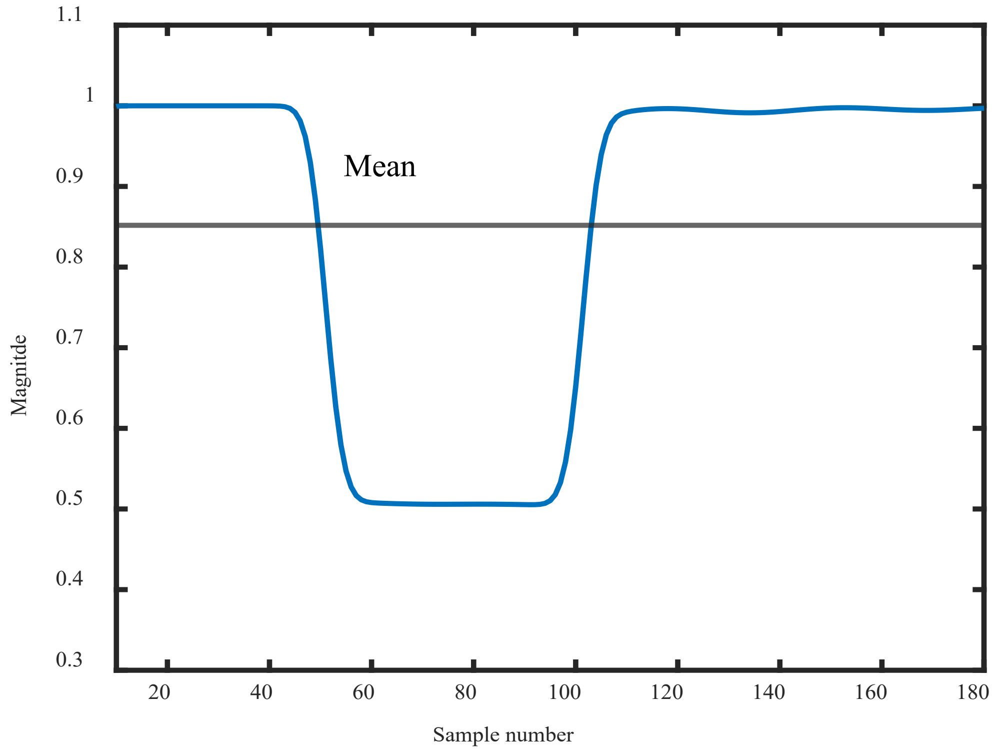
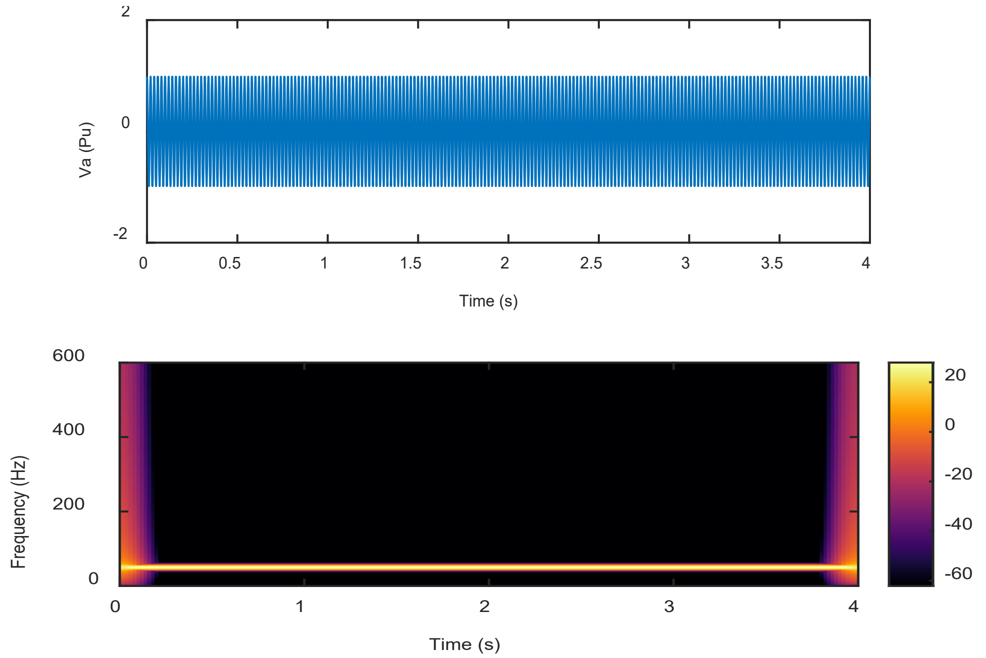


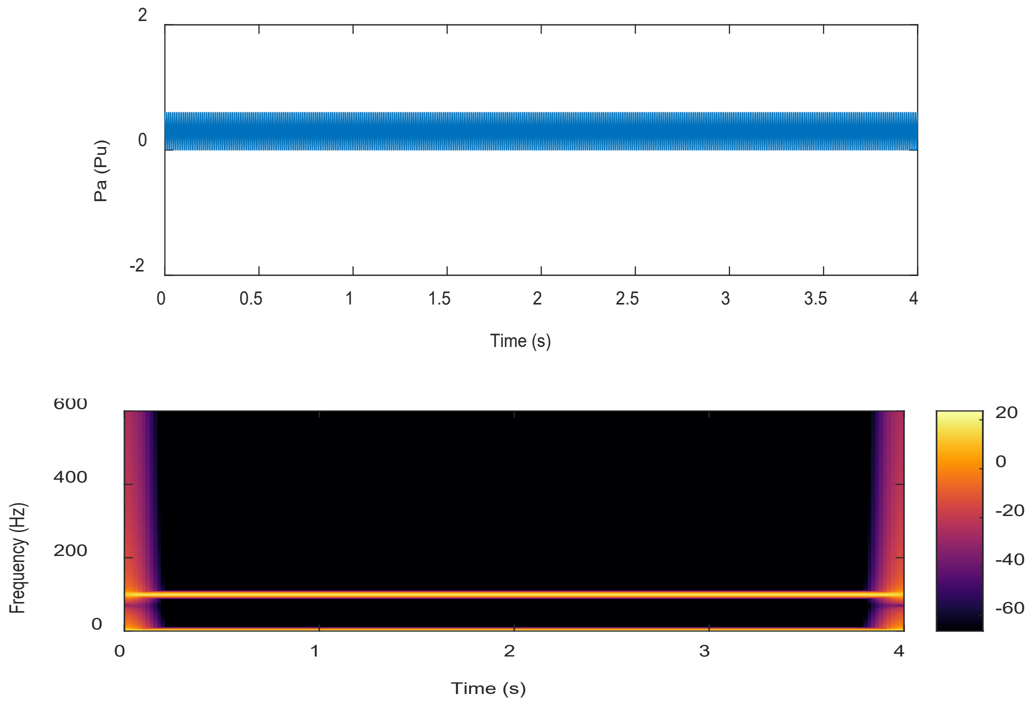
Figure 3.6: Mean value of R

3.3.3 Time-Frequency Representation of GT

Numerous events, both islanding, and non-islanding cases are processed using GT; the time localization of each frequency component of the processed signal provides compelling evidence for each event. The following figures from Figure 3.7 till Figure 3.14 depict the GT's response to these events.

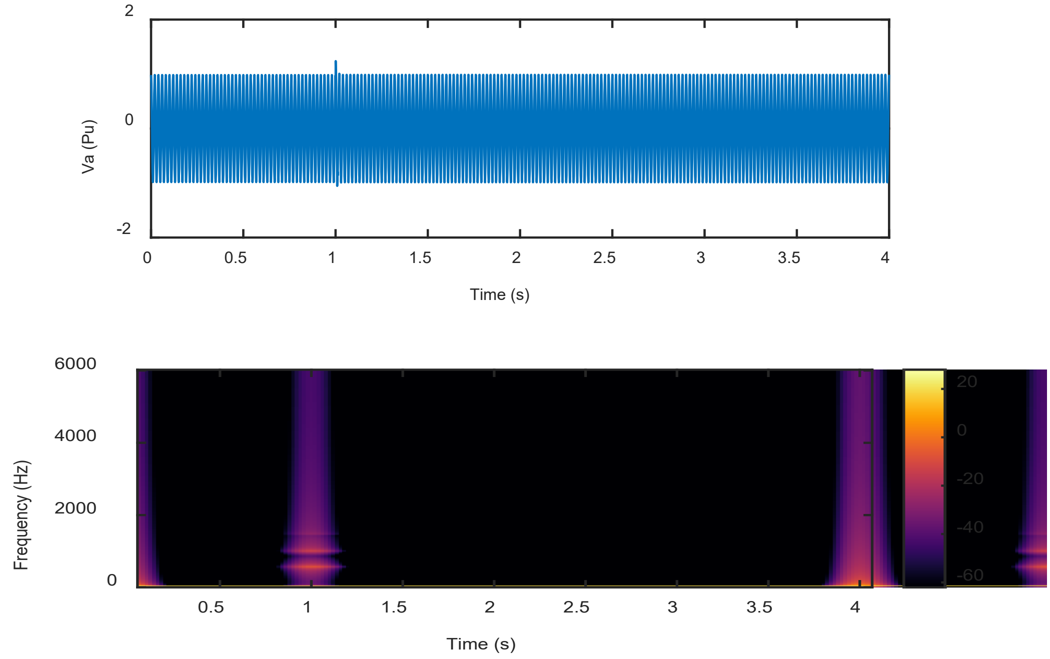


(a)

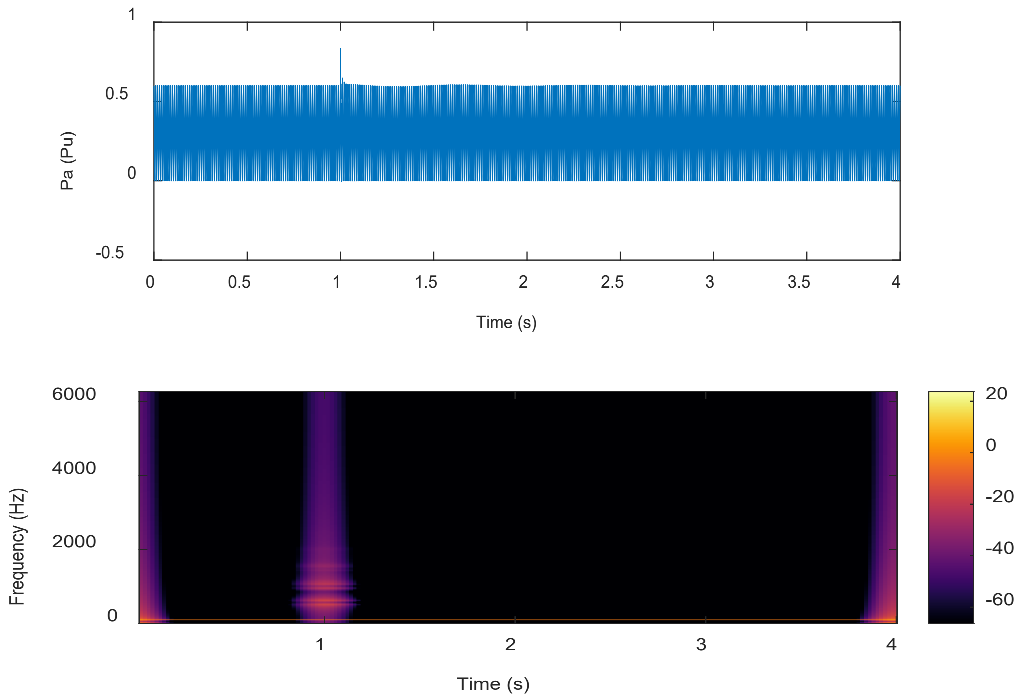


(b)

Figure 3.7: Normal operation. (a) GT response of the voltage signal for phase A. (b) GT response of the instantaneous power per phase for phase A signal

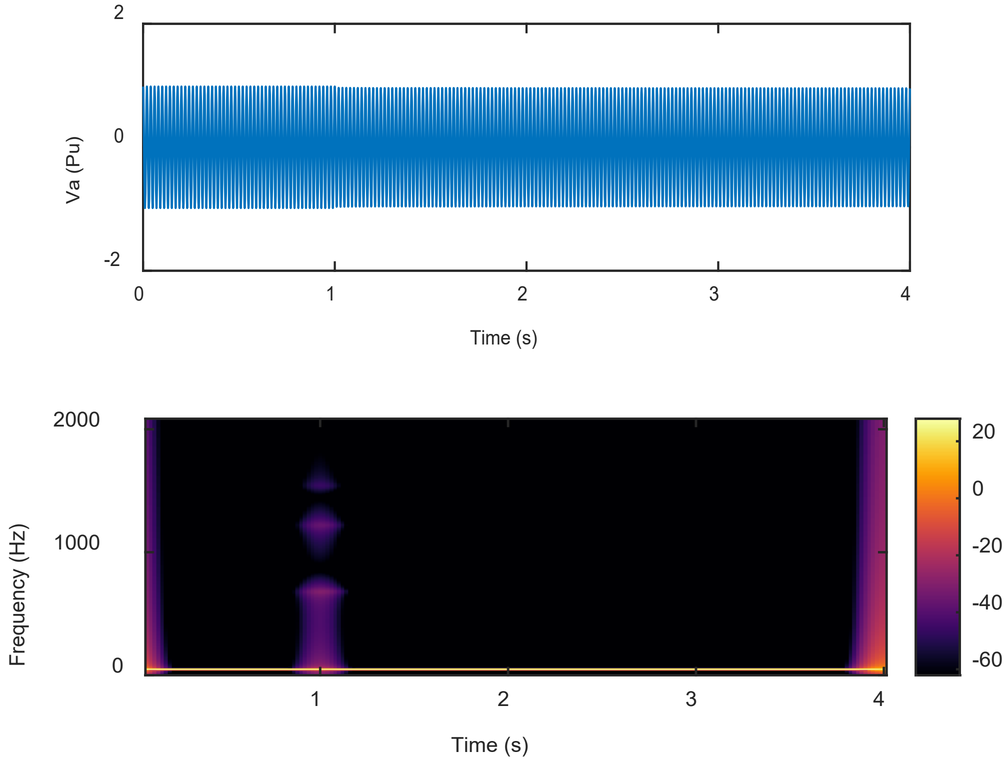


(a)

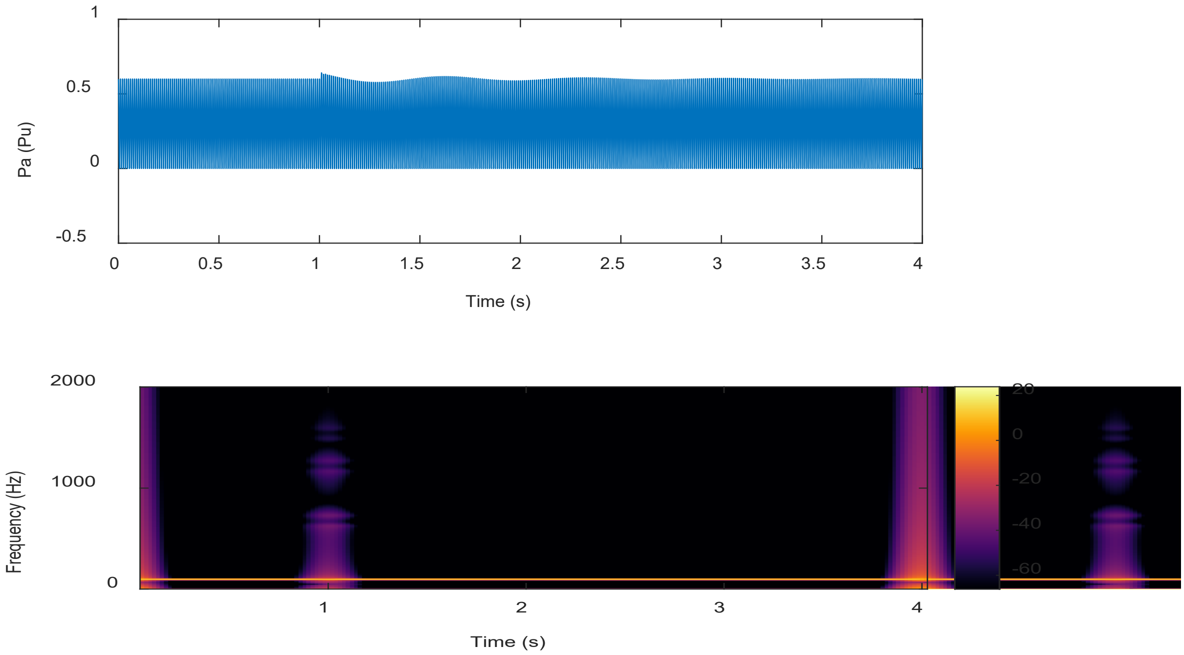


(b)

Figure 3.8: Capacitor switching. (a) GT response of the voltage signal for phase A. (b) GT response of the instantaneous power per phase for phase A signal

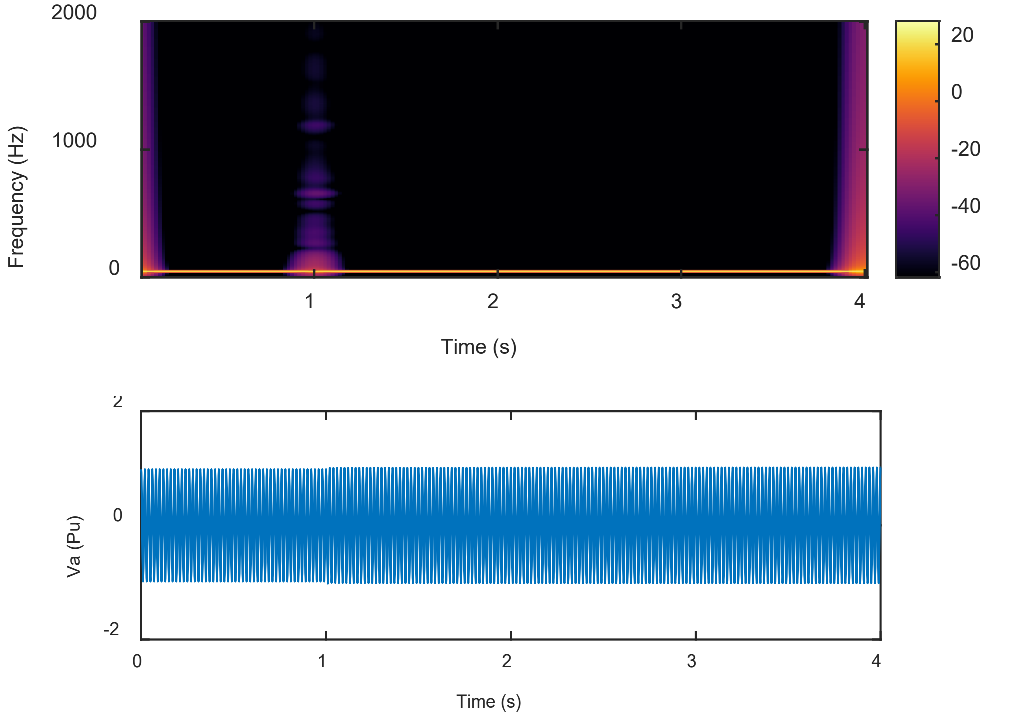


(a)

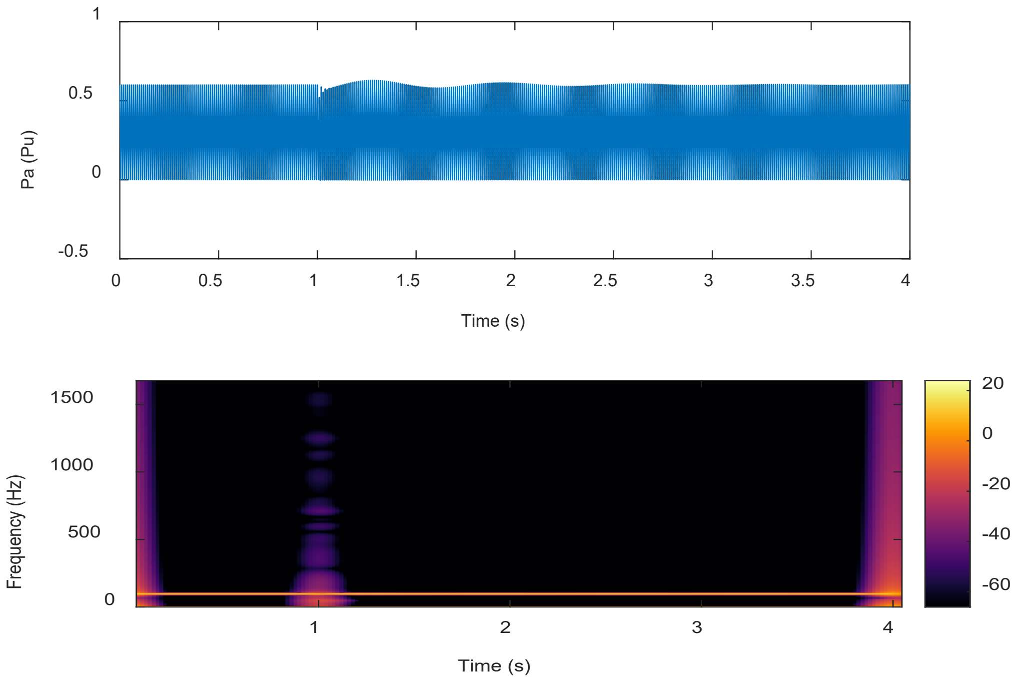


(b)

Figure 3.9: Adding load event to the system. (a) GT response of the voltage signal for phase A. (b) GT response of the instantaneous power per phase for phase A signal

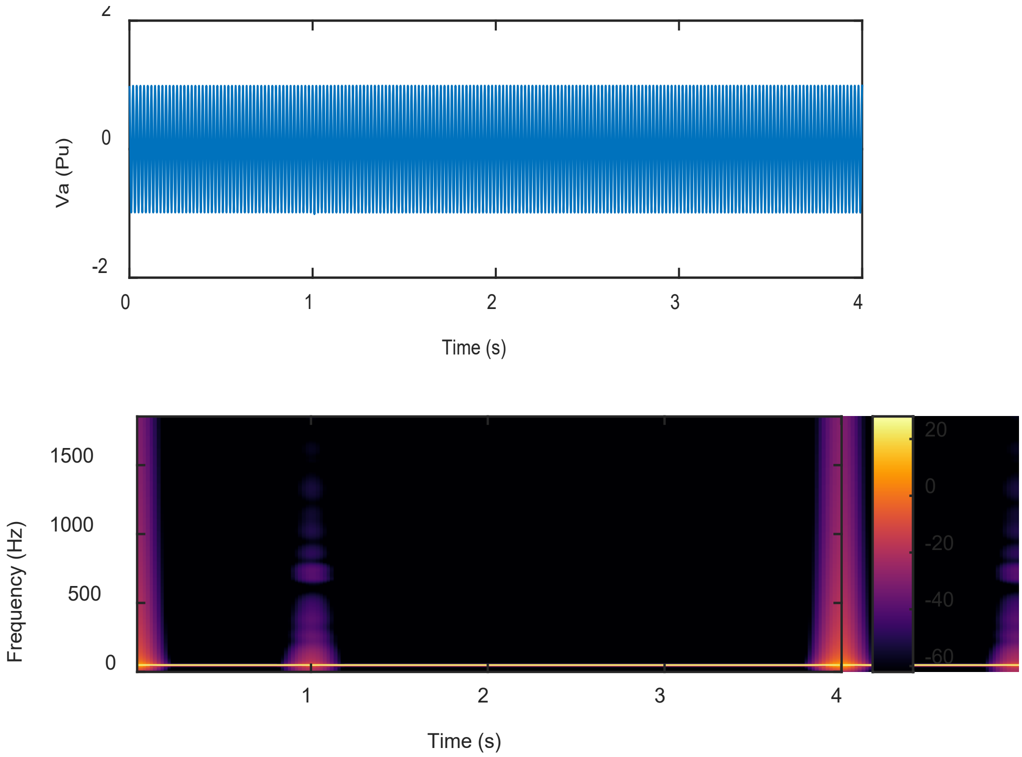


(a)

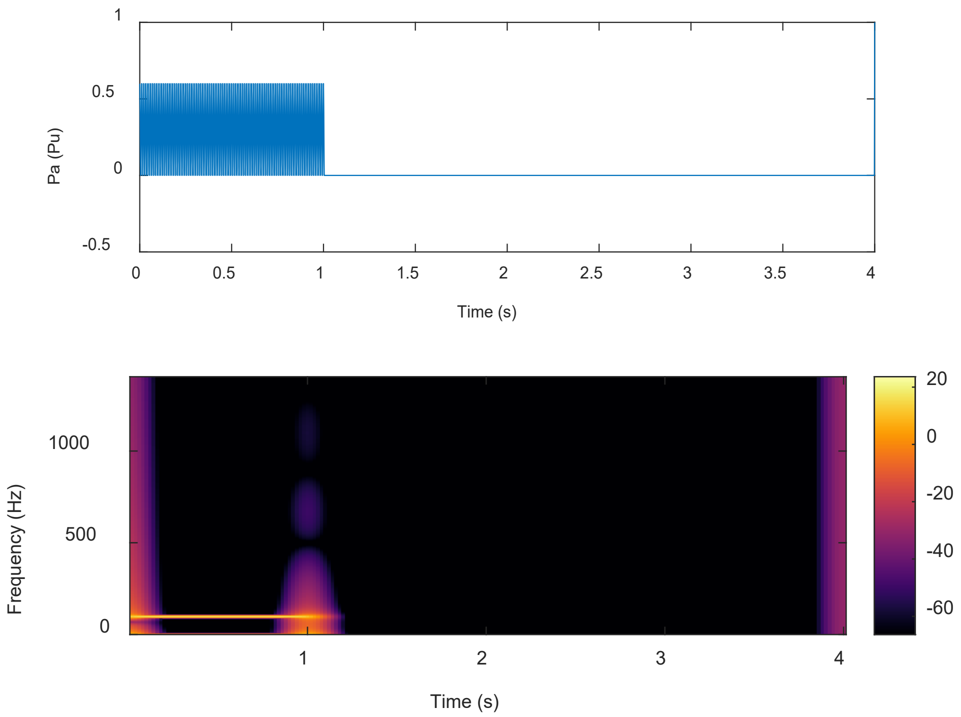


(b)

Figure 3.10: Removing load from the system. (a) GT response of the voltage signal for phase A. (b) GT response of the instantaneous power per phase for phase A signal

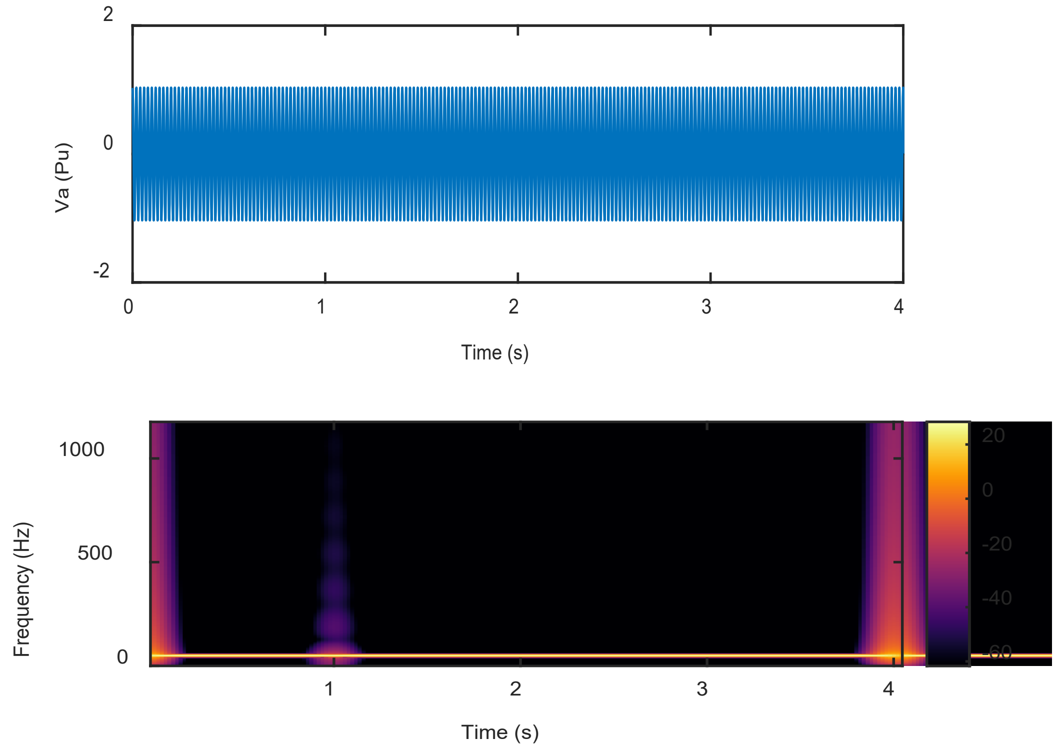


(a)

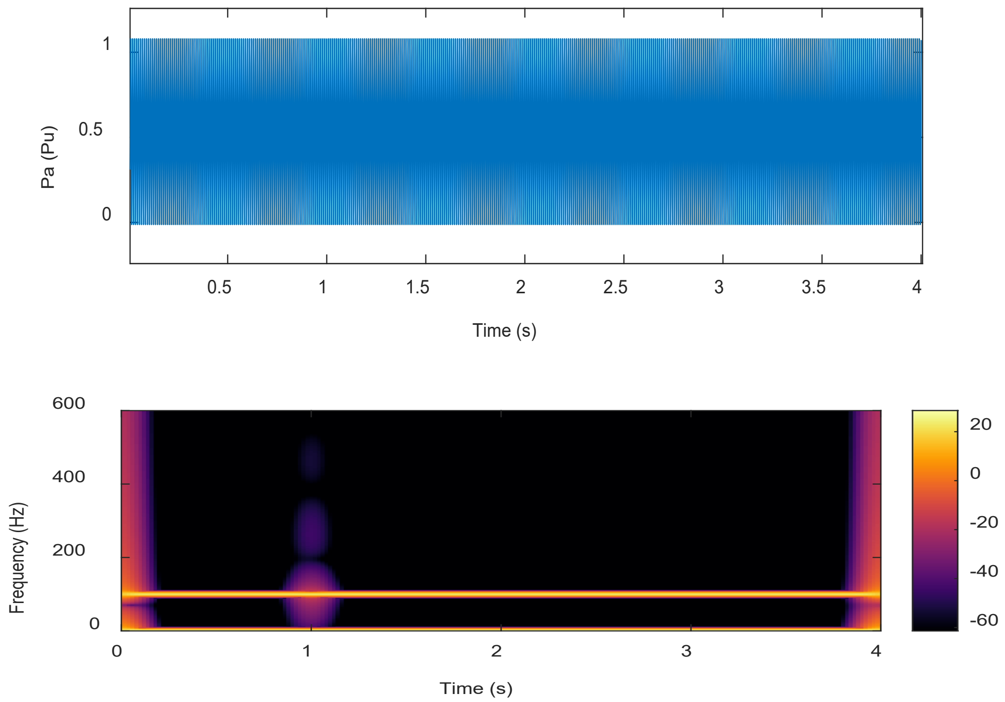


(b)

Figure 3.11: Tripping event. (a) GT response of the voltage signal for phase A. (b) GT response of the instantaneous power per phase for phase A signal

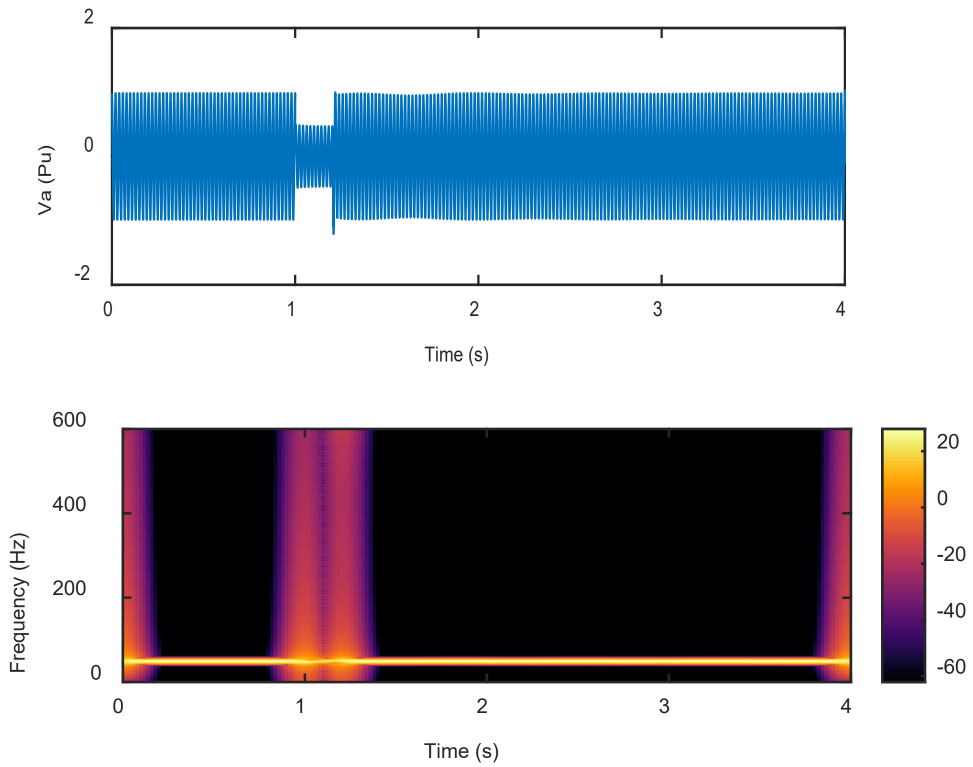


(a)

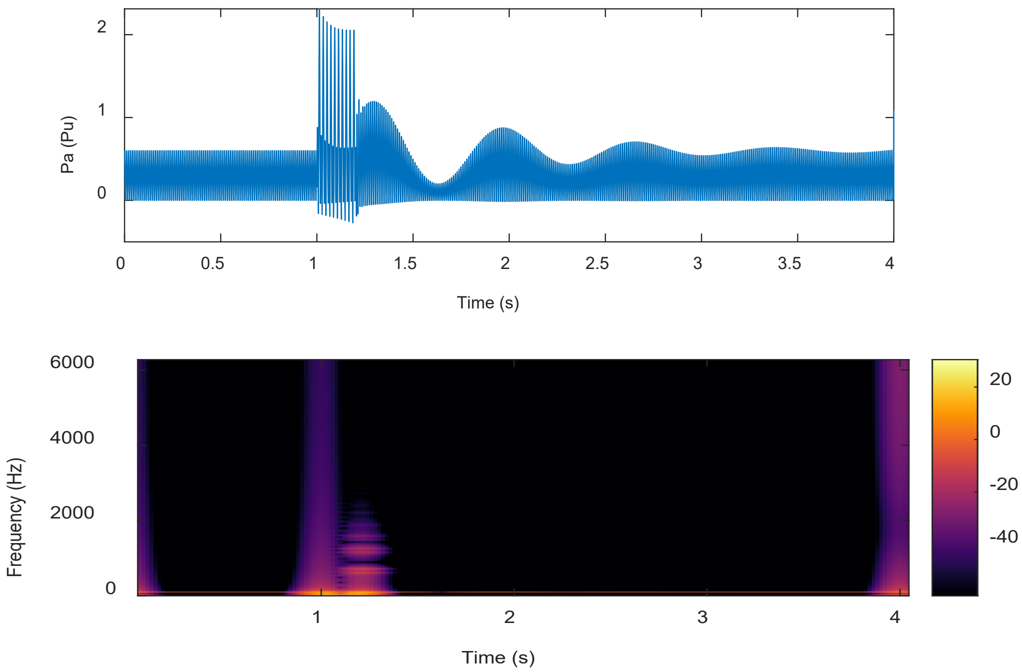


(b)

Figure 3.12: Islanding event with zero power mismatch. (a) GT response of the voltage signal for phase A. (b) GT response of the instantaneous power per phase for phase A Signal



(a)



(b)

Figure 3.13: Line to line fault. (a) GT response of the voltage signal for phase A. (b) GT response of the instantaneous power per phase for phase A signal

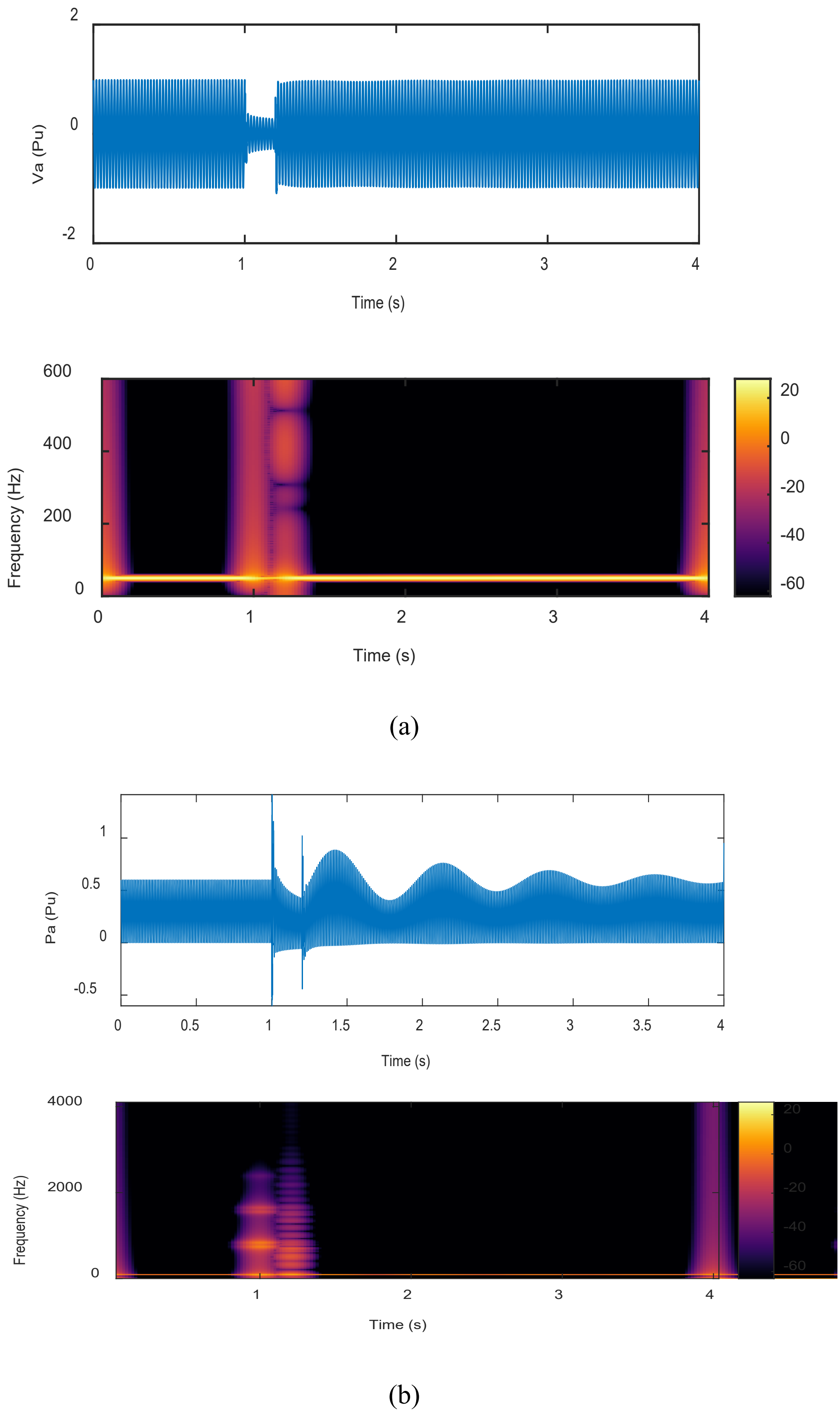


Figure 3.14: Three phase fault. (a) GT response of the voltage signal for phase A. (b) GT response of the instantaneous power per phase for phase A signal

3.3.4 Design of the AI Classifier

Data samples for training and testing as well as input parameter sets are essential for artificial intelligence classifiers like the RF. The GT characteristics covered in the preceding sections can be used as input to the classifier for numerous disturbance events. Table 3.1 demonstrates the output of the classifier for training or target parameters, such as islanding or non-islanding conditions, which can be acquired through simulation and assigning a value to each event. Each classifier can be developed as described in Figure 3.15. The number of classifiers required is determined by the number of DG units connected to the network. So the proposed method can be applicable in the large-scale distribution systems with several distributed generation units by serving each DG unit with separate intelligent classifier. For each classifier, the training data samples account for up to 75% of total data samples, with the remaining 25% being used for testing and validation. So, the final output decision of the classifier (Y1, Y2, Y3,...Yn) will be the target number that describes the type of event.

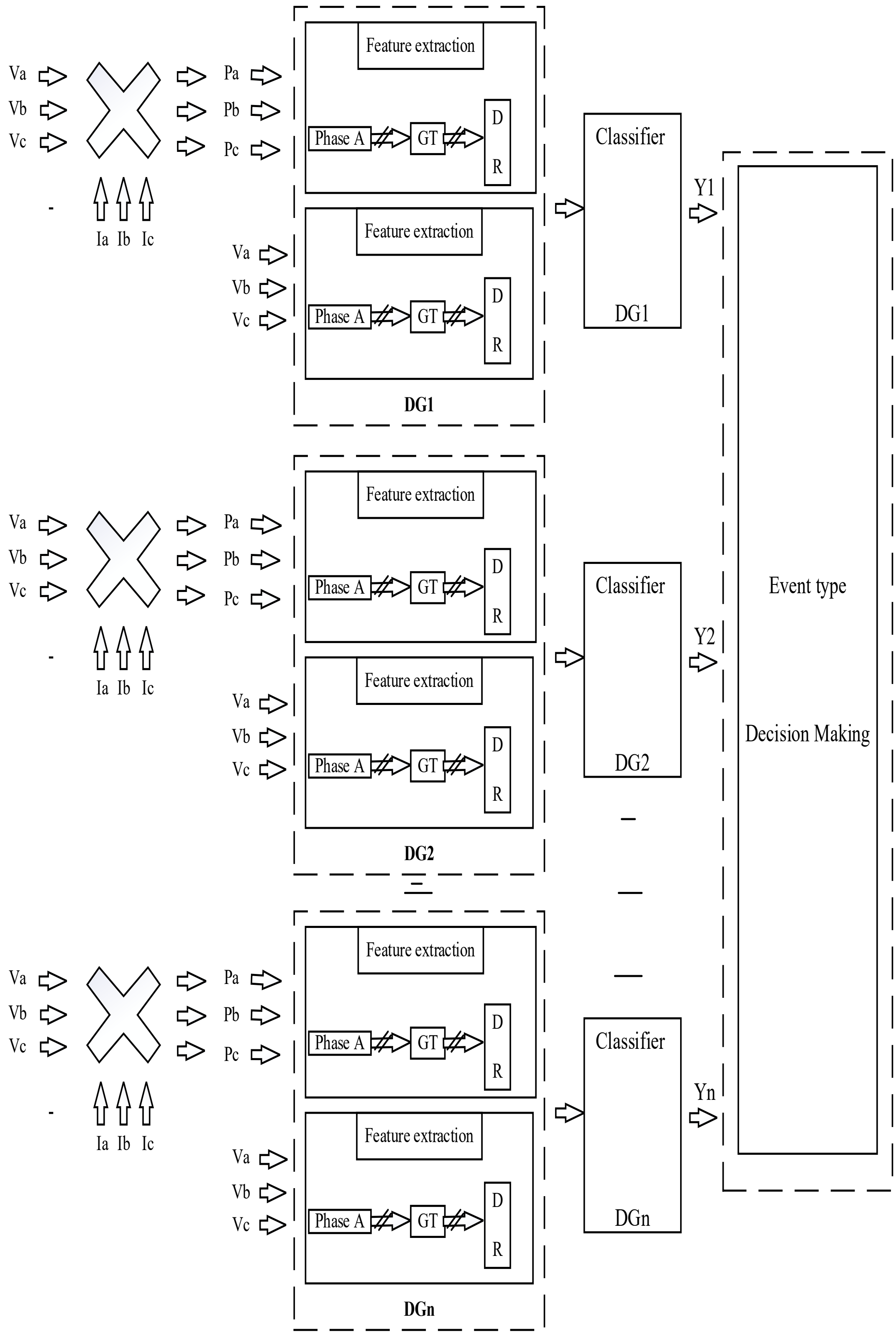


Figure 3.15: Summary of GT-based classifier

The overall implementation phases of the proposed approach outlined above can be summarized as follows, and in a flowchart as shown in Figure 3.16.

Step 1: Design the test system using DIgSILENT Power Factory® software.

Step 2: Apply numerous power quality events, such as Tripping events, load switching, capacitor switching, faults, and islanding cases in the system using the simulation model

Step 3: Record the voltage and instantaneous power per phase waveform at each DG terminal for all of the simulated disturbance events with the predefined event class identifier given in Table 3.1.

Step 4: Extract the features using the GT technique as described in Section 3.3.

Step 5: Train the CatBoost classifier using the training data and the five GT features as described in Sections 3.3.2 and 3.3.3. In this thesis, three types of classifiers are used, namely, CatBoost, RF and MLP. The training part is conducted via an offline process. These classifiers will yield eight outputs. The number of classifiers depends on the number of units DGs in the test system model.

Step 6: For new inputs, detect type of event using the trained network.

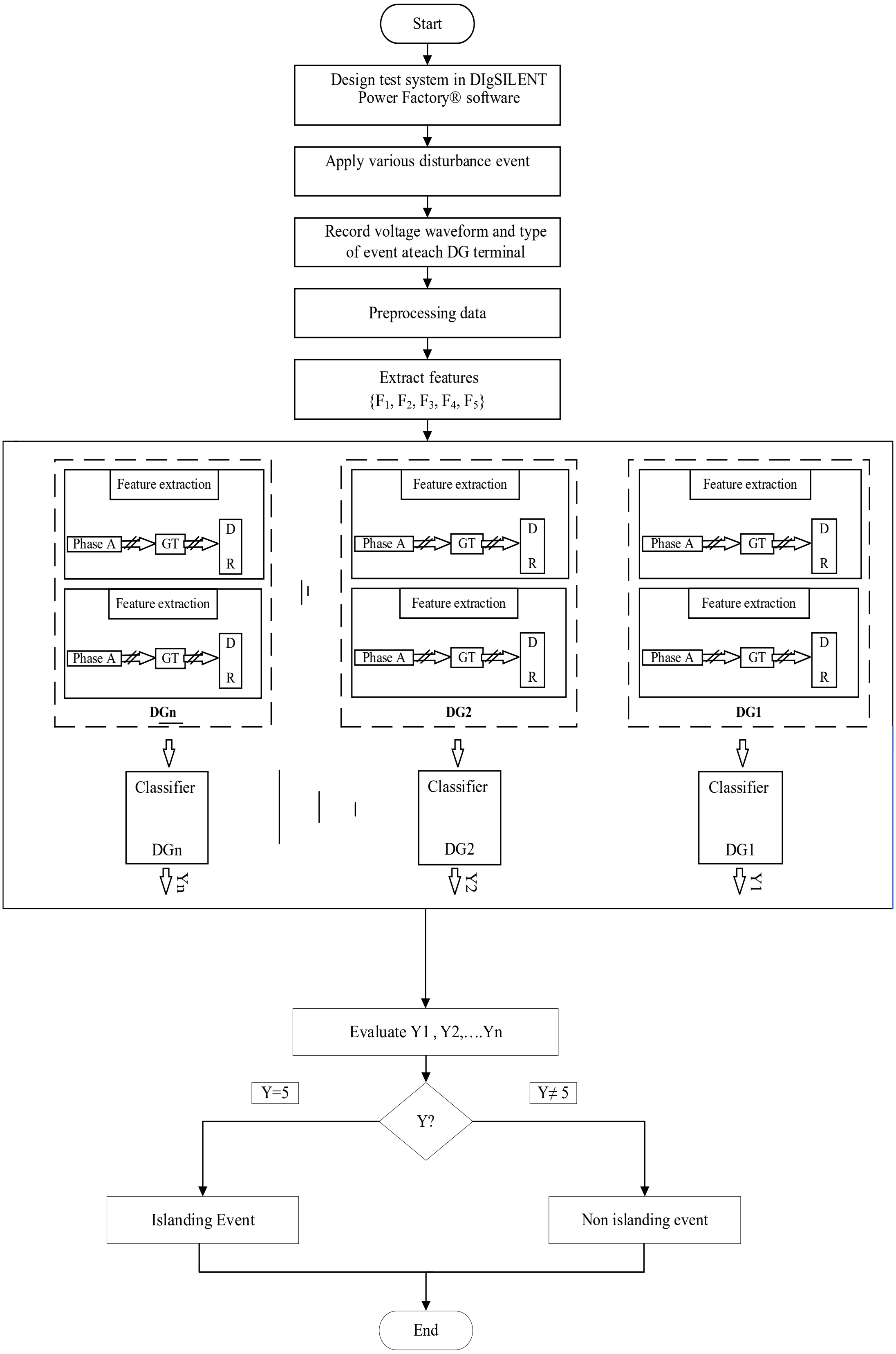


Figure 3.16: Implementation steps of GT-based islanding detection using CatBoost scheme

3.4 Performance Evaluation Methods

The performance of the proposed islanding detection technique must first be evaluated to assess its effectiveness and accuracy. This part demonstrates the performance assessment methods, compares the conventional technique to the proposed method, and introduces the statistical indices used to determine the proposed method's prediction accuracy.

3.4.1 Performance Evaluation of Conventional Methods

The RF and MLP based islanding detection schemes given in [81] and [82] are utilized to evaluate the performance of the proposed method. The flowchart for implementing the conventional approaches in islanding detection and classification scheme is sho in Figure 3.17. Also, the implementation procedures are described as follows:

Step 1: Design the test system using DIgSILENT Power Factory® software.

Step 2: Apply numerous power quality events, such as Tripping events, load switching, capacitor switching, faults, and islanding cases in the system using the simulation model.

Step 3: Record the voltage and instantaneous power per phase waveform at each DG terminal for all of the simulated disturbance events with the predefined event class identifier given in Table 3.1.

Step 4: Extract the features using the GT technique as described in Section 3.3.

Step 5: Train the RF and MLP classifier using the training data and the five GT features as described in Sections 3.3.2 and 3.3.3. In this thesis, three types of classifiers are used, namely, CatBoost, RF and MLP. The training part is conducted via an offline process. These classifiers will yield eight outputs. The number of classifiers depends on the number of units DGs in the test system model.

Step 6: For new inputs, detect type of event using the trained network.

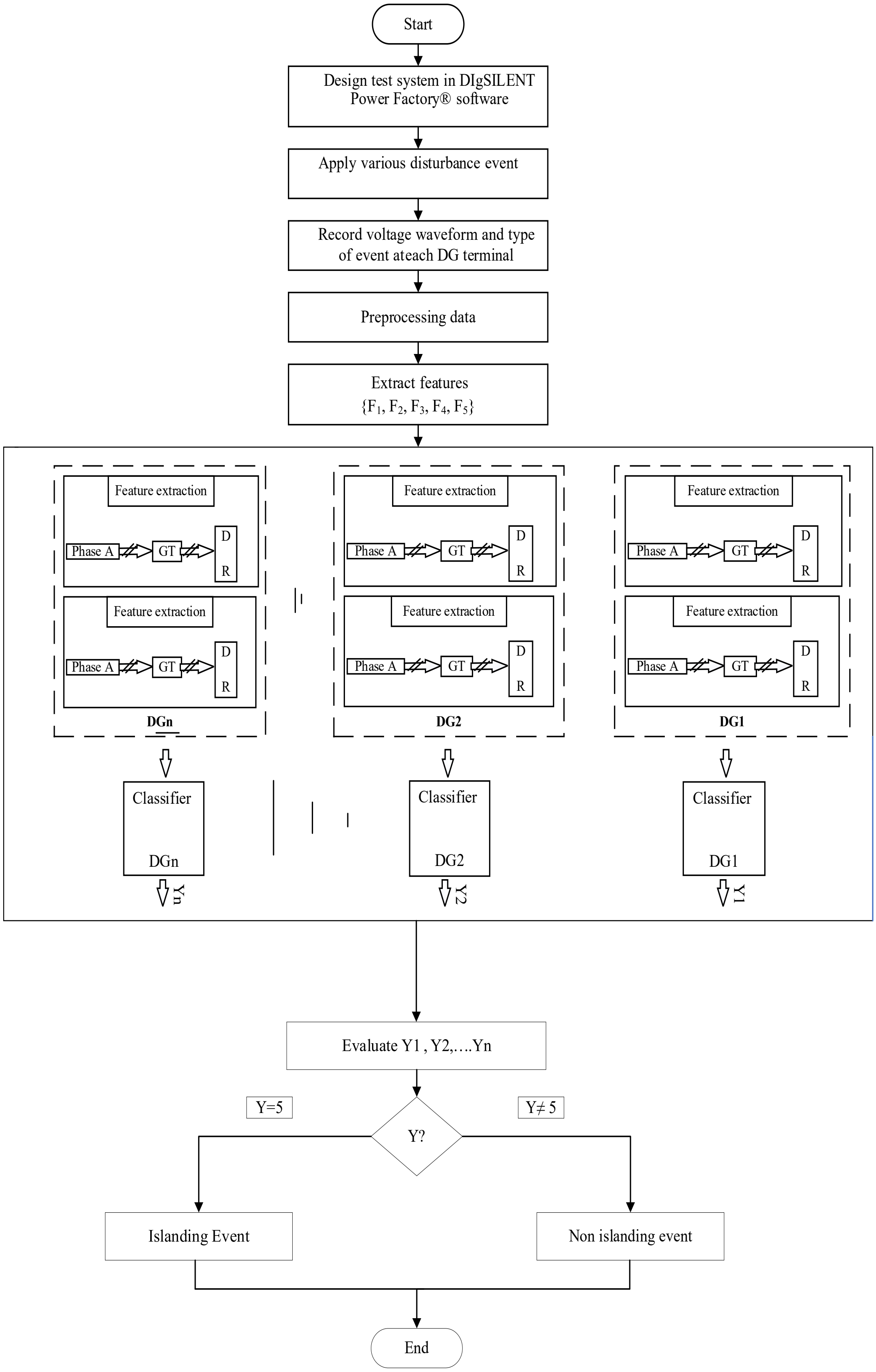


Figure 3.17: Implementation steps of GT-based islanding detection using MLP/RF schemes

3.4.2 Performance Evaluation with Various Indices

The performance evaluation metrics are used to determine how well-trained machine learning models perform. This enables you to determine how much better your machine learning model performs on a dataset it has never encountered before. For this purpose, accuracy (F1-score), root mean squared error (RMSE Binary), area under curve (AUC), feature importance and training time are used to predict the performance of the islanding detection and classification. These variables can be derived as follows:

i. Accuracy is a classification model metric that represents the proportion of correct predictions to the total number of predictions made.

$$Accuarcy = \frac{\#\ of\ correct\ predictions}{\#\ of\ total\ predictions} \qquad \text{Equation (14)}$$

ii. AUC is the measure of the ability of a classifier to distinguish between classes. The higher the AUC, the better the performance of the model at distinguishing between the classes. Table 3.4 illustrates Scale of judgment of AUC.

Table 3.4: Scale of judgment of AUC

AUC	**Judgment of Prediction**
1	Perfectly distinguish between all the class points correctly.
0	Distinguish all the class points wrongly
0.5<AUC<1	High chance to distinguish the class points correctly

3.5 Conclusion

This chapter discusses a methodology for detecting and classifying islands using GT as a feature extraction approach. The CatBoost classifier is fed with the characteristics collected from the three-phase voltage and the instantaneous power per phase signals measured at DG terminals. The number of classifiers in the system is dependent on the number of DGs. Numerous metrices are provided to assess the proposed islanding detection method's performance. The performance evaluation technique compares the conventional neural network method to the suggested method and evaluates the results using numerous factors. This chapter also discusses the implementation processes for the proposed islanding detection system and the standard technique scheme.

Chapter 4: Results and Discussion

4.1 The Test System for Islanding Detection

A radial distribution system consisting of two identical DG units is selected to validate the suggested approach for islanding detection, the model used in [57] since it is based on real-world data.

4.1.1 Radial Distribution System with Two Identical DG Units

The radial distribution system with two identical DG units is illustrated in Figure 4.1. The system is powered by a 120 kV, 1000 MVA source at a 50 Hz frequency. The DG units are simulated using synchronous machines and are located within 30 km of a distribution π--sections line model [57]. Table 4.1 includes details about the studied system.

Table 4.1: System model parameters [57]

Parameter	Description
External Grid	Represented by a 120 kV, 1000 MVA source
L1	Load with 15 MW and 3 MVar
L2&L3	Load with 8 MW and 3 MVar
DG1 & DG2	1200 V_{dc}
T1	Transformer 120/25 kV
T2 & T3	Transformer 25/0.6 kV
Line 1	25 kV with 10 km length
Line 2 & Line 3	25 kV with 20 km length
PCC	Point of common coupling
A&B	Point near by the respective DG (A is point near DG1; B is point near DG2)

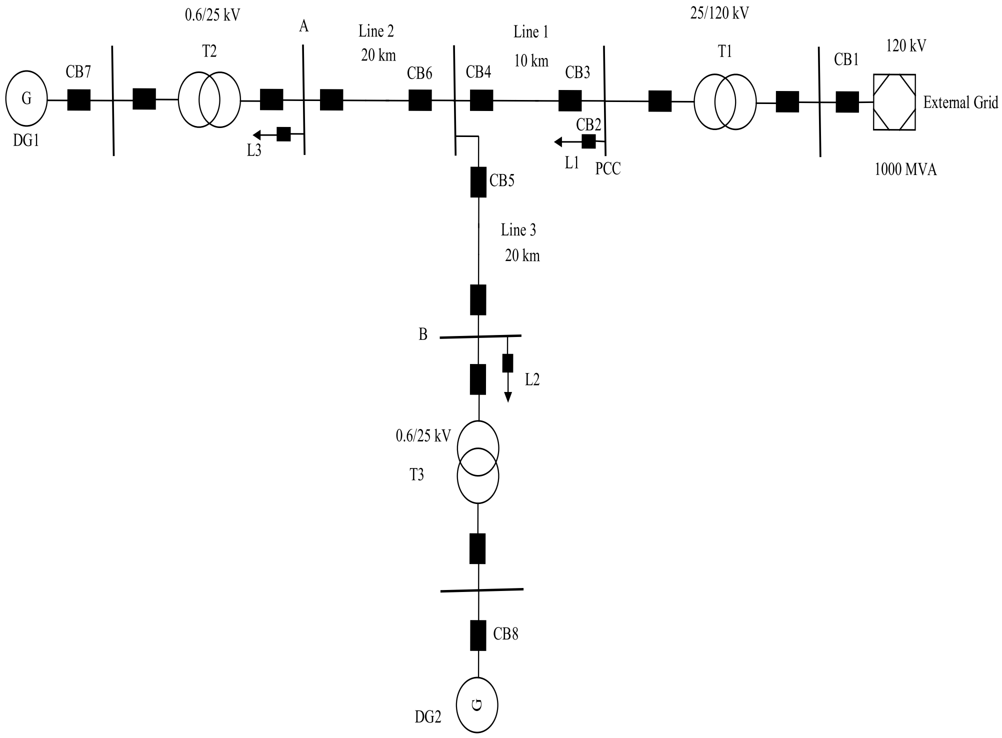


Figure 4.1: Distribution systems with two DG units [57]

4.2 Test Results of the Radial Distribution System with two Identical Distributed Generations units

This section describes the results of testing the suggested approach for islanding detection on a radial distribution system with two identical DG units. The following scenarios are considered in the simulations:

i. Capacitor switching and load switching at PCC points and DGs units.

ii. Faults at PCC point, DGs units, and distribution lines.

iii. Loss of mains at the PCC bus.

iv. Tripping of the main circuit breaker for islanding condition.

v. Tripping of other DGs apart from the target one.

vi. Events that can trip breakers and reclosers, as well as island the DG under study such as tripping distribution lines.

The accompanying conditions are simulated using the DIgSILENT Power Factory® program under a variety of operational settings:

a) Normal DG loading, minimum DG loading, and maximum DG loading.

b) Various operating points of the DG that causes NDZ.

The radial distribution system with two identical DGs can form three islands and can be tested with three possible NDZ conditions (Figure 4.2) by varying loading setpoints of consumer and DGs [83].

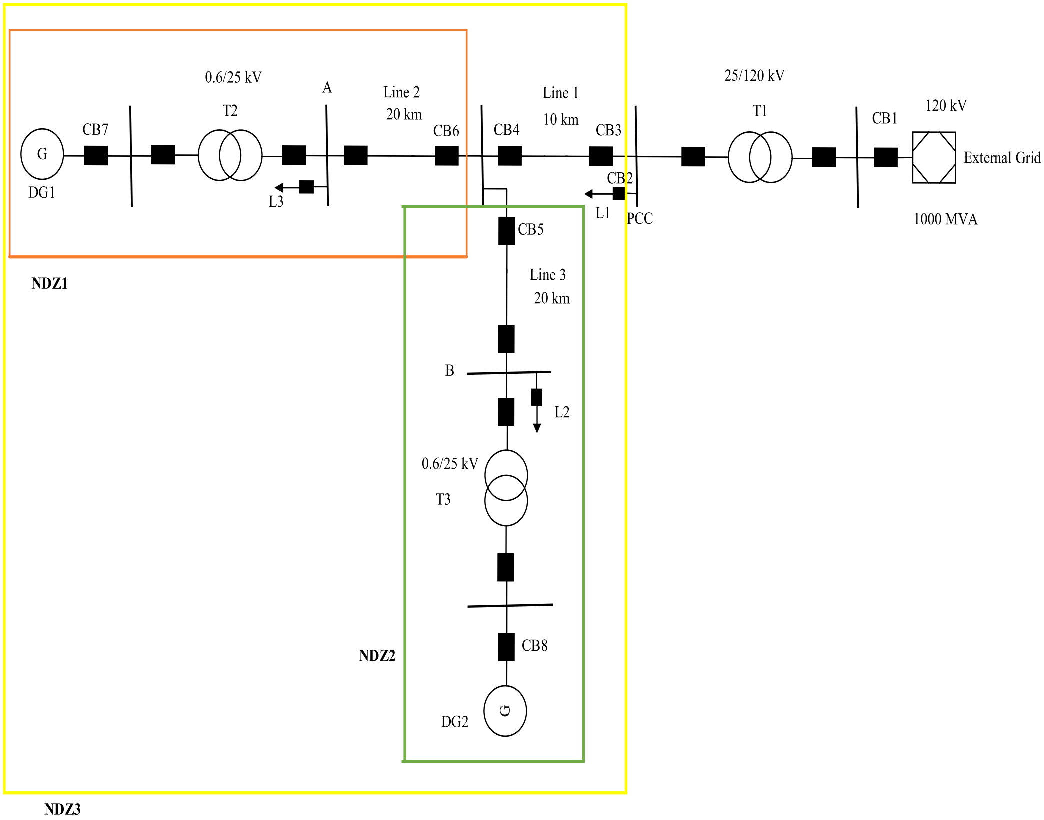


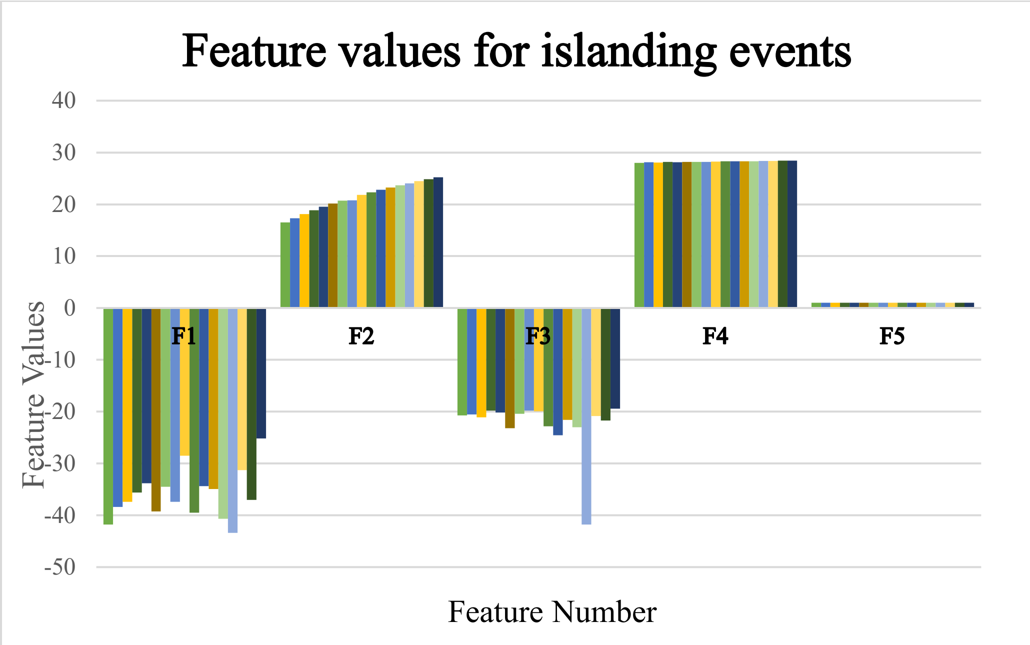
Figure 4.2: Possible islands and NDZ regions in the radial distribution system withtwo DG units

4.2.1 Input Features Extraction

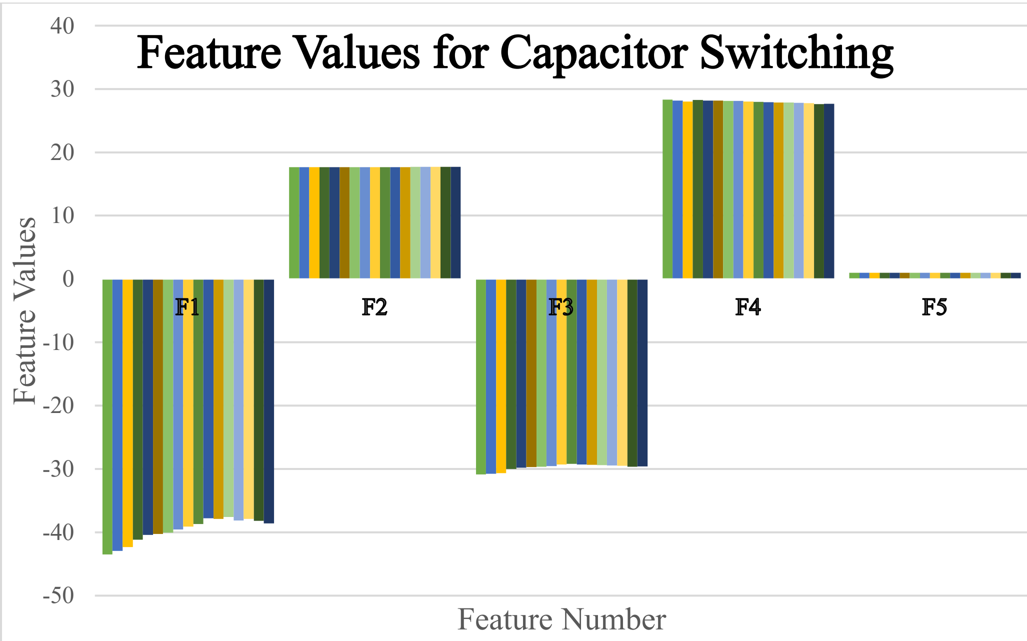
As described in Chapter 3, Figure 4.3 illustrates the samples of input features obtained for islanding and non-islanding event detection using the GT approach for the target DG. As shown in Figure 4.3 (a), the feature values for islanding events range from -41.7669 to -25.1491, 16.4839 to 25.2006, -41.7984 to -19.4178, 28.0043 to 28.4485 and 0.9999 to 1.0001 for F1, F2, F3, F4, and F5, respectively. These feature value combinations, and their associated ranges are notably different than those associated with non-islanding events, such as capacitor bank switching and phase to phase fault events (Figure 4.3 (b) and (c)). The feature values for capacitor bank switching events range from -43.5031 to -37.5772, 17.642 to 17.6945, -30.8625 to -29.208, 27.6016 to 28.3354, and 1.0014 to 1.0035 for F1, F2, F3, F4, and F5, respectively, whereas those for phase to phase fault events range from -8.8438 to -7.9587, 22.2778 to 23.359, -1.893 to -1.0344, 25.9814 to 26.7486, and 0.9652 to 0.9654 for F1, F2, F3, F4, and F5, respectively. Thus, the unique case features such as islanding and all other non-islanding events serve as crucial inputs for intelligent classifiers such as CatBoost, RF, and neural networks.

Numerous islanding and non-islanding conditions are tested with the test system to collect multiple data sets. Since the test system has two DG units, it requires two classifiers to determine the class of events in both islanding and non-islanding events. The classifiers use 442 samples, which correspond to training and testing. This demonstrates the distribution of training and testing data utilized to develop the islanding detection algorithm. As shown in Table 4.2, 338 samples (75%) are used for training, whereas 104 samples (25%) are applied for testing and validation. The CatBoost, Rf, and MLP algorithms are implemented as an islanding detection classifier using the Python program. And in all the classifier designs, the default setting parameters are used to make fair comparison. Meanwhile, the same training and testing data are utilized to model all the classifiers. Table 4.3 illustrates function names and initialization parameters used for the CatBoost, RF, and MLP classifiers of the target

DG.

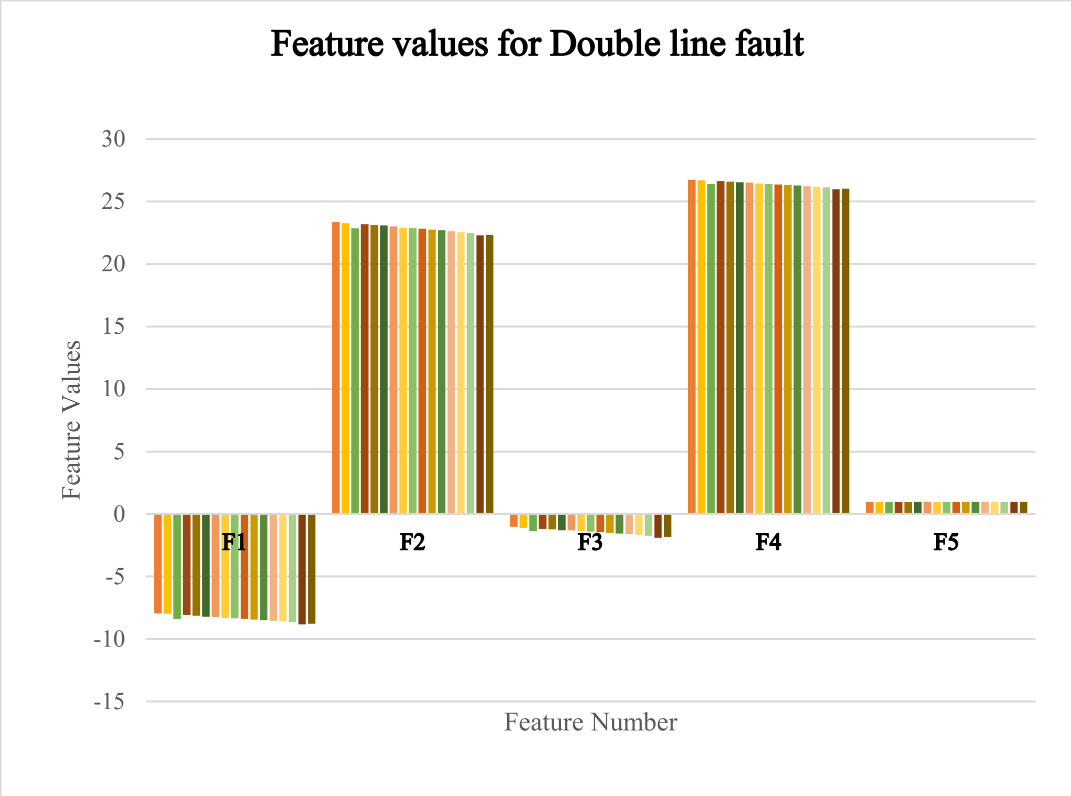


(a)



(b)

Figure 4.3: Samples of selected GT features for islanding and non- islanding events at the target DG in the studied system. (a) Islanding condition. (b) Capacitor switching events (Non-Islanding condition). (c) Phase to phase fault events (non-islanding condition)



(c) Phase to phase fault events (non-islanding condition)

Figure 4.3: Samples of selected GT features for Islanding and non- Islanding events at the target DG in the studied system. (a) Islanding condition. (b) Capacitor switching events (Non-Islanding condition). (c) Phase to phase fault events (non-islanding condition) (continued)

Table 4.2: Number of samples for training and testing

Data Types	Number of Sample Data		
	CatBoost	**RF**	**MLP**
Training	338	338	338
Testing	104	104	104

Table 4.3: Parameter settings of the MLP, RF and Catboost classifiers for the target DG

`	**MLP**	**RF**	**CatBoost (Default Settings)**	**CatBoost after Tuning**
Main Package	sklearn.neural_network	sklearn.ensemble	CatBoost.CatBoostClassifier	CatBoost. CatBoostClassifier
Training Data (Training Intrinsic)	256x5	256x5	256x5	256x5
Validation Data (Training Intrinsic)	82x5	82x5	82x5	82x5
Testing Data	104x5	104x5	104x5	104x5
Iterations	max_iter = 1000	n_estimators = 100 &1000	Iterations = 1000	Iterations = 800
Accuracy Metric	F1 Score	F1 Score	F1 Score & AUC	F1 Score & AUC
Tree/Layer Arch.	Hidden layers =15	Tree depth = 9	Tree depth = 6	Tree depth = 7

4.2.2 Result of GT with MLP Classifier

The performance of MLP with GT features for islanding detection and classification was evaluated using various data after being trained offline. These testing results include a variety of disturbance scenarios, including islanding and non-islanding events under normal and NDZ settings. The training time of the MLP classifier was higher than other classifiers with a value equal to 1.4 s. To check the accuracy of the classifier, the output results of the MLP classifier are then compared to actual or anticipated target values. Table 4.4 shows the accuracy of the GT feature decision-making with the MLP classifier and the performance comparison of the output with the goal data. According to Table 4.4, the classifier can detect 25% of the islanding class. While for non-islanding events, the accuracy is 59.3%.

Table 4.4: MLP Classification results with GT features

Classes	Number of Cases	Number of Sample Data	
		Correct Detection	Accuracy (%)
Non-Islanding	96	57	59.3
Islanding	8	2	25

4.2.3 Result of GT with RF Classifier

Using similar procedures with GT features combined with an MLP classifier, the MLP is replaced with an RF classifier and is trained and tested with GT features. These testing results include the same disturbance scenarios, including islanding and non-islanding events under normal and NDZ settings. Figure 4.4 illustrates the RF tree at the last iteration and all the related metrics are described in the figure. The five features (F1, F2, F3, F4 and F5) are represented by (x(0), x(1), x(2), x(3) and x(4)) respectively. The training time for the RF classifier is 1.2 s. The output results of the RF classifier are then compared to actual or anticipated target values. Table 4.5 shows the accuracy of the GT feature decision-making and the performance comparison of the output with the goal data. And the classifier can detect 75% of the islanding class. While for non-islanding events, the accuracy is 95.8%.

Table 4.5: RF Classification results with GT features

Classes	**Number of Cases**	**Number of Sample Data**	
		Correct Detection	**Accuracy (%)**
Non-Islanding	96	92	95.8
Islanding	8	6	75

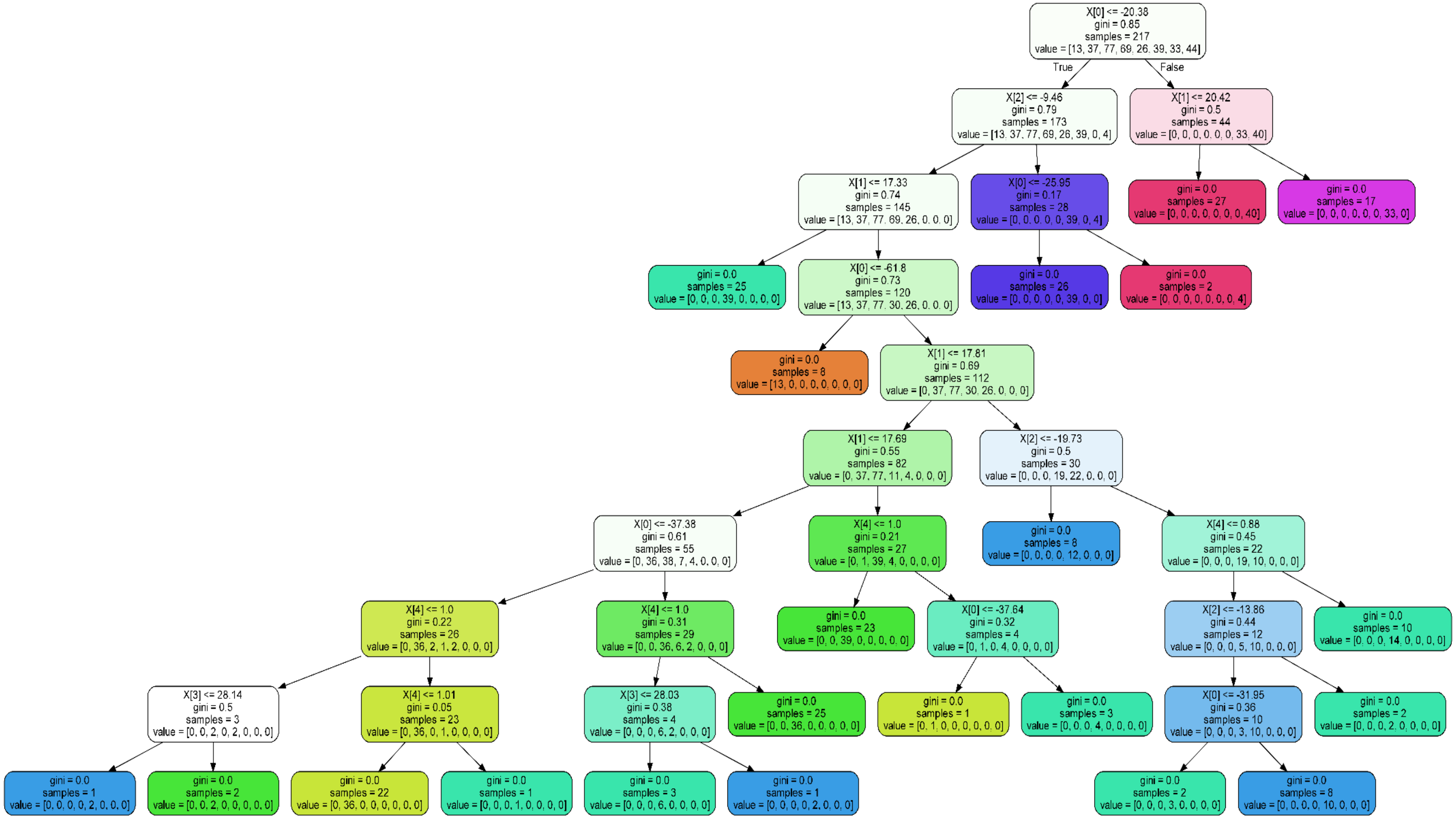


Figure 4.4: RF tree at the last iteration

4.2.4 Result of GT with CatBoost Classifier

To improve the performance of the islanding detection algorithm with the previous classifiers, the MLP and RF classifiers are replaced with a CatBoost classifier by maintaining the same training and testing data. Two models are used in the proposed method. The first model is with the default settings, and the second model is a tuned model that selects the best parameters (tree depth, learning rate, and the number of iterations) automatically. Figure 4.5 demonstrates the best parameter settings of the tuned model.

The two models are compared with each other using the AUC metric, as shown in Figure 4.6 the CatBoost model with the default setting is described using the blue line, while the tuned model is illustrated using the red line. The tuned model reached an AUC value of 1 after around 65 iterations. On the other hand, more iterations are needed for the default model to reach 1 AUC. The training time is approximately 0.88 s, which is less than other classifiers' training times. The most important features which affect the training process for the tuned model are F1, F2, and F5 with 23.27, 22.28, and 23.24 percent, respectively, while F3 and F4 account for 19.6% and 11.59%. Table 4.6 shows the accuracy of the GT feature decision-making combined with the CatBoost classifier and the performance comparison of the output with the goal data. The classifier can detect 75% of the island cases. The accuracy for non-islanding events is 98.9 percent. Another metric called RMSE binary is illustrated in Figure 4.7 for 1000 iterations of the tuned model.

Table 4.6: CatBoost classification results with GT features

Classes	Number of Cases	Number of Sample Data	
		Correct Detection	Accuracy (%)
Non-Islanding	96	95	98.9
Islanding	8	6	75

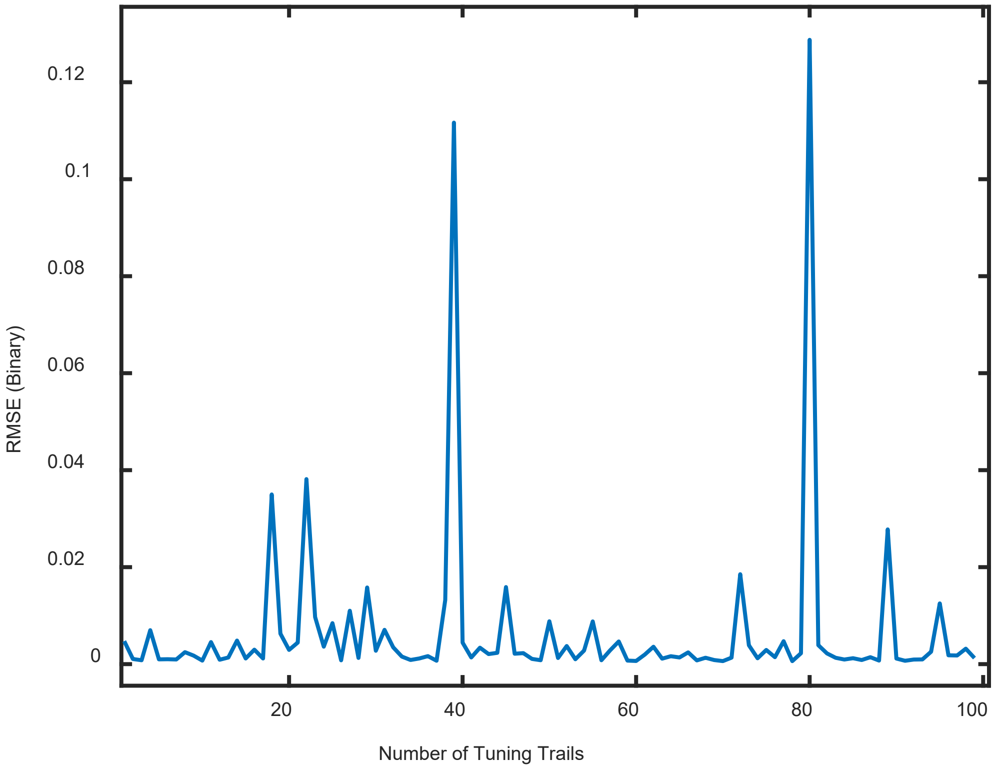


Figure 4.5: Selection of the parameter settings for the tuned model

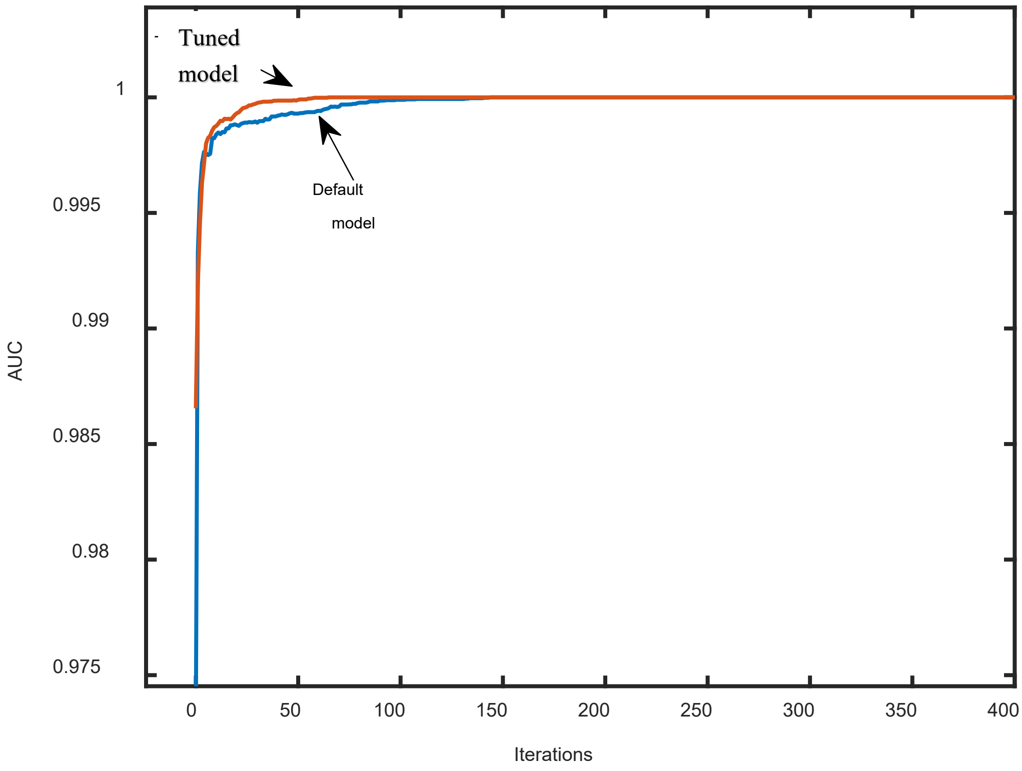


Figure 4.6: AUC of the default and tuned CatBoost classifier

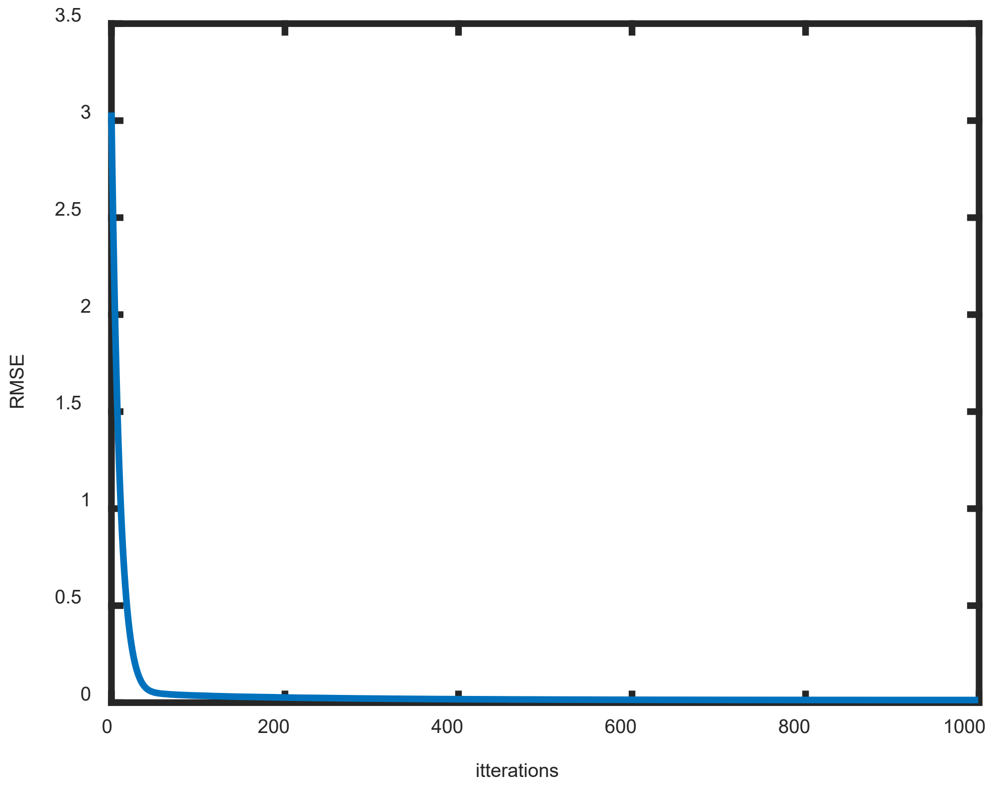


Figure 4.7: Binary RMSE of CatBoost model after tuning

4.2.5 Summary of the Results Obtained for all Tested Islanding Detection Methods

The overall classification accuracy of the CatBoost classifier is 97.1 percent for islanding and non-islanding conditions. However, only 94.23 and 54.8 percent accuracies are confirmed for the RF and MLP classifier for the islanding and non-islanding detection, respectively. The training time of the MLP, RF and CatBoost classifier are 1.4 s, 1.21 s, and 0.88 s respectively. The time needed by the classifier to detect the event is less than one cycle. Therefore, it can be assumed a fast detection algorithm. Table 4.7 summarizes the overall accuracies of all the methods and the training time needed for each classifier.

Table 4.7: Comparison of classifiers' performance

Classifier Type	**Number of Cases**	**Number of Sample Data**		
		Correct Detection	**Accuracy (%)**	**Training Time**
CatBoost	104	101	97.1	0.88 s
RF	104	98	94.2	1.21 s
MLP	104	57	54.8	1.39 s

The test results shown in Table 4.7 highlight the following points:

i. The CatBoost classifier technique provides a higher overall accuracy compared with the other classifiers.
ii. The training time of the CatBoost classifier is less than other classifiers.
iii. The GT Features are effective in classification and islanding detection and can provide unique data for the classifier.

4.3 Chapter Summary

This chapter presents the main issue related to the formation of islanded systems with DGs. And the developed islanding detection scheme in Chapter 3 is validated through comparison with other proposed methods by using the radial distribution system with two identical DG units. To assess the effectiveness and robustness of the proposed technique, some metrics and indices are evaluated and analyzed.

Chapter 5: Conclusions and Recommendations

5.1 Overall Conclusion

This thesis covers the development of islanding detection for distributed generation-integrated radial distribution systems. This research has two objectives, namely, 1) to develop a reliable and accurate method of islanding detection that can accurately identify the islanding condition. 2) to evaluate and compare the suggested islanding detection scheme with the currently available techniques. To accomplish the first objective, a novel islanding detection scheme based on GT feature extraction combined with a CatBoost classifier has been developed. For this study, various events, including islanding and non-islanding cases such as types of faults, capacitor switching, and load switching, are simulated using DIgSILENT Power Factory® software. The three-phase voltage signals are measured at the DG terminal and the instantaneous power per phase is determined to be processed. Feature extraction based on the GT technique is subsequently used to extract special features for islanding and non-islanding cases. These features are used as the input for the CatBoost classifier, which then classifies the islanding cases.

The proposed technique is initially simulated using a simple radial distribution system with two identical DG units. The simulation results indicate that the GT feature extraction with the CatBoost algorithm can be utilized as an islanding detection technique. To achieve the second objective, performance evaluation with various metrics and conventional techniques is conducted to validate the proposed islanding detection scheme. For the islanding detection study, the accuracy of the proposed technique is validated by comparing it with the conventional islanding detection technique. The test results indicate that the GT feature extraction combined with the

CatBoost classifier can significantly improve performance concerning conventional islanding detection algorithms. Moreover, it is a more effective and robust technique than the GT feature combined with the RF and MLP classifiers. The proposed method can be enhanced by using more data to train the classifier. So, it's more accurate in comparison with active techniques and other techniques. All the research objectives are met, and the results are robust and effective. The development of the proposed method in this research meets a recent need to be able to detect islanding in radial distribution systems with DGs.

5.2 Significant Contributions of the Research

This thesis's main contribution can be summarized in the following points:

a) Currently, no research has employed GT as a feature extraction method and CatBoost as Intelligent classifier for islanding detection in power systems. Therefore, GT feature extraction combined with the CatBoost algorithm provides a novel method for islanding detection.

b) For islanding detection, the suggested GT feature extraction technique using the CatBoost algorithm outperforms previous algorithms. The simulation results also show that GT feature extraction with CatBoost is a more effective and robust technique than other conventional techniques using the Rf and MLP classifiers.

5.3 Recommendations for Future Studies

This thesis proposes a novel method for islanding detection for distributed generation-integrated radial distribution systems.

1) The Modified p-q theory can be used combined with the proposed method.

2) The islanding detection scheme in this study is passive technique. an Active technique combined with the proposed method can be considered in future studies.
3) Instead of using CatBoost as the classification technique, the multivariate regression analysis can be utilized with the GT extraction feature to classify the events.

References

[1] J. A. Cebollero, D. Cañete, S. Martín-Arroyo, M. García-Gracia, and H. Leite, "A Survey of Islanding Detection Methods for Microgrids and Assessment of Non-Detection Zones in Comparison with Grid Codes," *Energies*, vol. 15, no. 2, 460, 2022. doi: https://doi.org/10.3390/en15020460.

[2] B. K. Panigrahi, A. Bhuyan, J. Shukla, P. K. Ray, and S. Pati, "A comprehensive review on intelligent islanding detection techniques for renewable energy integrated power system," *International Journal of Energy Research*, vol. 45, no. 10. John Wiley and Sons Ltd, pp. 14085–14116, Aug. 01, 2021. doi: https://doi.org/10.1002/er.6641.

[3] F. Chanaa *et al.*, "Islanding Detection Method of a Photovoltaic Installation Destined to Power a RLC Load and Integrated to LV Network," *International Journal of Intelligent Engineering and Systems*, vol. 14, no. 4, pp. 299–311, Aug. 2021. doi: https://doi.org/10.22266/ijies2021.0831.27.

[4] A. Khamis, H. Shareef, and A. Mohamed, "Islanding detection and classification and load shedding scheme for dispersed generation integrated radial distribution systems," Universiti Kebangsaan Malaysia Bangi, 2013. doi: https://doi.org/10.1049/iet-gtd.2015.0263.

[5] D. Velasco, C. L. Trujillo, G. Garcerá, and E. Figueres, "Review of anti-islanding techniques in distributed generators," *Renewable and Sustainable Energy Reviews*, vol. 14, no. 6. pp. 1608–1614, Aug. 2010. doi: https://doi.org/10.1016/j.rser.2010.02.011.

[6] A. Khamis, H. Shareef, E. Bizkevelci, and T. Khatib, "A review of islanding detection techniques for renewable distributed generation systems," *Renewable and Sustainable Energy Reviews*, vol. 28. pp. 483–493, Dec. 2013. doi: https://doi.org/10.1016/j.rser.2013.08.025.

[7] J. Yin, L. Chang, S. Member, and C. Diduch, "Recent developments in islanding detection for distributed power generation." In: 2004 Large Engineering Systems Conference on Power Engineering (IEEE Cat. No. 04EX819). IEEE, 2004. p. 124–128 doi:https://doi.org/10.1109/LESCPE.2004.1356285.

[8] T. Adrian, O. Alexandre, and N. M. H. Carl, "Islanding detection in smart grids.," in *2010 IEEE Energy Conversion Congress and Exposition*, Oct. 2010, pp. 3631–3636. doi: https://doi.org/10.1109/ECCE.2010.5618306.

[9] B. Dob and C. Palmer, “Communications Assisted Islanding Detection Contrasting Direct Transfer Trip and Phase Comparison Methods,” in *2018 71st Annual Conference for Protective Relay Engineers (CPRE)*, Oct. 2018, pp. 1–6. doi: https://doi.org/10.1109/CPRE.2018.8349783.

[10] B-álvarez, I. J, H.-G. Kim, F. Z. Peng, and Ortiz-rivera, “Survey of Distributed Generation Islanding Detection Methods,” *IEEE Latin America Transactions*, vol. 8, no. 5, pp. 565–570, 2010. doi: https://doi.org/10.1109/TLA.2010.5623510.

[11] A. Khamis, H. Shareef, E. Bizkevelci, and T. Khatib, “A review of islanding detection techniques for renewable distributed generation systems,” *Renewable and Sustainable Energy Reviews*, vol. 28, pp. 483–493, Dec. 2013. doi: https://doi.org/10.1016/j.rser.2013.08.025.

[12] C. R. Reddy and K. H. Reddy, “Islanding Detection Techniques for Grid Integrated Distributed Generation-A Review,” *International Journal of Renewable Energy Research* , vol. 9, no. 2, pp. 960–977, 2019.

[13] S. il Jang and K. H. Kim, “An islanding detection method for distributed generations using voltage unbalance and total harmonic distortion of current,” *IEEE Transactions on Power Delivery*, vol. 19, no. 2, pp. 745–752, Apr. 2004. doi: https://doi.org/10.1109/TPWRD.2003.822964.

[14] H. H. Zeineldin, E. F. El-Saadany, and M. M. A. Salama, “Impact of DG interface control on islanding detection and nondetection zones,” *IEEE Transactions on Power Delivery*, vol. 21, no. 3, pp. 1515–1523, Jul. 2006. doi: https://doi.org/10.1109/TPWRD.2005.858773.

[15] A. Dube and A. Sindhu, “Comparative analysis of passive islanding detection methods for grid-connected Distrubted Generators,” 2015. doi: https://doi.org/10.1109/INDICON.2015.7443138.

[16] O. Ozgonenel, S. Karagol, O. Ozgonenel, and ; S Karagol, “Islanding Detection in Photo-Voltaic Systems Based on Instantaneous Power Measurements,” *International Journal Of Renewable Energy Research*, vol. 7, no. 4, pp. 1723–1730, May 2017.

[17] T. Zheng, H. Yang, R. Zhao, Y. C. Kang, and V. Terzija, “Design, evaluation and implementation of an islanding detection method for a micro-grid,” *Energies (Basel)*, vol. 11, no. 2, 323, Feb. 2018. doi: https://doi.org/10.3390/en11020323.

[18] F. Harirchi, R. Hadidi, M. Babakmehr, and M. G. Simões, “Advanced Three-Phase Instantaneous Power Theory Feature Extraction for Microgrid Islanding and Synchronized Measurements,” 2019. doi: https://doi.org/10.1109/SGSMA.2019.8784694.

[19] U. K. Jhuma, S. Mekhilef, M. Mubin, S. Ahmad, M. Rawa, and Y. Alturki, “Hybrid Islanding Detection Technique for Malaysian Power Distribution System,” in *2020 IEEE 5th International Conference on Computing Communication and Automation, ICCCA 2020*, Oct. 2020, pp. 785–790. doi: https://doi.org/10.1109/ICCCA49541.2020.9250847.

[20] P. Maha, Z. Chen, and B. B. Jensen, “Review on Islanding Operation of Distribution System with Distributed Generation,” 2011. doi: https://doi.org/10.1109/PES.2011.6039299.

[21] H. Karimi, A. Yazdani, and R. Iravani, “Negative-sequence current injection for fast islanding detection of a distributed resource unit,” *IEEE Transactions on Power Electronics*, vol. 23, no. 1, pp. 298–307, Jan. 2008. doi: https://doi.org/10.1109/TPEL.2007.911774.

[22] F. Liu, Y. Kang, Y. Zhang, S. Duan, and X. Lin, “Improved SMS islanding detection method for grid-connected converters,” *IET Renewable Power Generation*, vol. 4, no. 1, pp. 36–42, 2010. doi: https://doi.org/10.1049/iet-rpg.2009.0019.

[23] C. H. Yoo, D. H. Jang, S. K. Han, D. Sung , and S. S. Hong, “A new phase drift anti-islanding method for grid-connected inverter system,” 2011. doi: https://doi.org/10.1109/ICPE.2011.5944637.

[24] H. H. Zeineldin, “A Q-f droop curve for facilitating islanding detection of inverter-based distributed generation,” *IEEE Transactions on Power Electronics*, vol. 24, no. 3, pp. 665–673, 2009, doi: https://doi.org/10.1109/TPEL.2008.2008649.

[25] Ch. Rami Reddy, B. Srikanth Goud, B. Nagi Reddy, M. Pratyusha, C. V. Vijay Kumar, and R. Rekha, “Review of Islanding Detection Parameters in Smart Grids,” 2020. doi: https://doi.org/10.1109/icSmartGrid49881.2020.9144923.

[26] V. Menon and M. H. Nehrir, “A hybrid islanding detection technique using voltage unbalance and frequency set point,” *IEEE Transactions on Power Systems*, vol. 22, no. 1, pp. 442–448, Feb. 2007. doi: https://doi.org/10.1109/TPWRS.2006.887892.

[27] C. W. Yeau, “A hybrid islanding detection method for distributed synchronous generators,” in *The 2010 International Power Electronics Conference - ECCE ASIA* -, 2010, pp. 1326–1330. doi: https://doi.org/10.1109/IPEC.2010.5544559.

[28] M. Khodaparastan, H. Vahedi, F. Khazaeli, and H. Oraee, “A Novel Hybrid Islanding Detection Method for Inverter-Based DGs Using SFS and ROCOF,” *IEEE Transactions on Power Delivery*, vol. 32, no. 5, pp. 2162–2170, Oct. 2017. doi: https://doi.org/10.1109/TPWRD.2015.2406577.

[29] S. Murugesan, V. Murali, and S. A. Daniel, “Hybrid Analyzing Technique for Active Islanding Detection Based on d-Axis Current Injection,” *IEEE Systems Journal*, vol. 12, no. 4, pp. 3608–3617, Dec. 2018. doi: https://doi.org/10.1109/JSYST.2017.2730364.

[30] D. Mlakić, S. Nikolovski, and H. R. Baghaee, “Hybrid Method for Islanding Detection of Distributed Generators in LV Distribution Networks,” 2019. doi: https://doi.org/10.1109/EUROCON.2019.8861902.

[31] G. Wang, “Design Consideration and Performance Analysis of a Hybrid Islanding Detection Method Combining Voltage Unbalance/Total Harmonic Distortion and Bilateral Reactive Power Variation,” *CPSS Transactions on Power Electronics and Applications*, vol. 5, no. 1, pp. 86–100, Mar. 2020. doi: https://doi.org/10.24295/CPSSTPEA.2020.00008.

[32] S. Kim, “Islanding Detection Technique using Grid-Harmonic Parameters in the Photovoltaic System,” in *Energy Procedia*, 2012, vol. 14, pp. 931–936. doi: https://doi.org/10.1016/j.egypro.2011.12.887.

[33] J. H. Kim, J. G. Kim, Y. H. Ji, Y. C. Jung, and C. Y. Won, “An islanding detection method for a grid-connected system based on the goertzel algorithm,” *IEEE Transactions on Power Electronics*, vol. 26, no. 4, pp. 1049–1055, 2011. doi: https://doi.org/10.1109/TPEL.2011.2107751.

[34] Z. Yanping, Y. Qiuxia, Z. Dezhong, W. Junjuan, and T. Yuexin, “A novel islanding detection method of distributed generator based on wavelet transform,” in *2008 International Conference on Electrical Machines and Systems*, Oct. 2008, pp. 2686–2688.

[35] S. C. Paiva, R. L. de A. Ribeiro, D. K. Alves, F. B. Costa, and T. de O. A. Rocha, “A wavelet-based hybrid islanding detection system applied for distributed generators interconnected to AC microgrids,” *International Journal of Electrical Power and Energy Systems*, vol. 121, 106032, Oct. 2020. doi: https://doi.org/10.1016/j.ijepes.2020.106032.

[36] A. Pigazo, V. M. Moreno, M. Liserre, and A. Dell'aquila, "Wavelet-Based Islanding Detection Algorithm for Single-Phase Photovoltaic (PV) Distributed Generation Systems," in *2007 IEEE International Symposium on Industrial Electronics*, 2007, pp. 2409–2413. doi: https://doi.org/10.1109/ISIE.2007.4374984.

[37] A. Pigazo, M. Liserre, R. A. Mastromauro, V. M. Moreno, and A. Dell'Aquila, "Wavelet-based Islanding detection in grid-connected PV systems," *IEEE Transactions on Industrial Electronics*, vol. 56, no. 11, pp. 4445–4455, 2009. doi: https://doi.org/10.1109/TIE.2008.928097.

[38] C. T. Hsieh, J. M. Lin, and S. J. Huang, "Enhancement of islanding-detection of distributed generation systems via wavelet transform-based approaches," *International Journal of Electrical Power and Energy Systems*, vol. 30, no. 10, pp. 575–580, Dec. 2008. doi: https://doi.org/10.1016/j.ijepes.2008.08.006.

[39] S.R. Samantaray, Trupti Mayee Pujhari, and B.D. Subudhi, "A new approach to islanding detection in distributed generations," 2009. doi: https://doi.org/10.1109/ICPWS.2009.5442689.

[40] U. D. Dwivedi, M. Basu, K. Gaughan, M. Hanif, and M. Basu, "Wavelet based islanding detection of DC-AC inverter interfaced DG systems," in *45th International Universities Power Engineering Conference UPEC2010*, Sep. 2010, pp. 1–5.

[41] R. Shariatinasab and M. Akbari, "New islanding detection technique for DG using discrete wavelet transform," in *2010 IEEE International Conference on Power and Energy*, Oct. 2010, pp. 294–299. doi: https://doi.org/10.1109/PECON.2010.5697593.

[42] W. G. Morsi, C. P. Diduch, and L. Chang, "A New Islanding Detection Approach Using Wavelet Packet Transform for Wind-Based Distributed Generation," 2010. doi: https://doi.org/10.1109/PEDG.2010.5545860.

[43] H. K. Karegar and B. Sobhani, "Wavelet transform method for islanding detection of wind turbines," *Renewable Energy*, vol. 38, no. 1, pp. 94–106, Feb. 2012. doi: https://doi.org/10.1016/j.renene.2011.07.002.

[44] P. Buduma, S. J. Pinto, and G. Panda, "Wavelet based Islanding Detection in a Three-Phase Grid Collaborative Inverter System using FPGA Platform," 2018. doi: https://doi.org/10.1109/IICPE.2018.8709550.

[45] M. El Azzaoui, "Islanding detection method for distributed generation with wavelet based nuisance tripping suppression," *Electric Power Systems Research*, vol. 199, 107366, Oct. 2021. doi: https://doi.org/10.1016/j.epsr.2021.107366.

[46] P. K. Ray, N. Kishor, and S. R. Mohanty, “S-transform based islanding detection in grid-connected distributed generation based power system,” 2010. doi: https://doi.org/10.1109/ENERGYCON.2010.5771754.

[47] P. K. Ray, S. R. Mohanty, and N. Kishor, “Disturbance detection in grid-connected distributed generation system using wavelet and S-transform,” *Electric Power Systems Research*, vol. 81, no. 3, pp. 805–819, Mar. 2011. doi: https://doi.org/10.1016/j.epsr.2010.11.011.

[48] S.R. Samantaray, A. Samui, and B. C. Babu, “S-transform based cumulative sum detector (CUSUM) for islanding detection in Distributed Generations”, 2010 *Joint International Conference on Power Electronics, Drives and Energy Systems & 2010 Power India*. pp. 1-6, 2010. doi: https://doi.org/10.1109/PEDES.2010.5712397.

[49] P. P. Mishra and C. N. Bhende, “Islanding detection using sparse S-transform in distributed generation systems,” *Electrical Engineering*, vol. 100, no. 4, pp. 2397–2406, Dec. 2018. doi: https://doi.org/10.1007/s00202-018-0727-3.

[50] S. Dutta, P. K. Sadhu, M. J. B. Reddy, and D. K. Mohanta, “Shifting of research trends in islanding detection method - a comprehensive survey,” *Protection and Control of Modern Power Systems*, vol. 3, no. 1. Springer, Dec. 01, 2018. doi: https://doi.org/10.1186/s41601-017-0075-8.

[51] V. L. Merlin, R. C. Santos, A. P. Grilo, J. C. M. Vieira, D. v. Coury, and M. Oleskovicz, “A new artificial neural network based method for islanding detection of distributed generators,” *International Journal of Electrical Power and Energy Systems*, vol. 75, pp. 139–151, Feb. 2016. doi: https://doi.org/10.1016/j.ijepes.2015.08.016.

[52] S. Raza, H. Mokhlis, H. Arof, K. Naidu, J. A. Laghari, and A. S. M. Khairuddin, “Minimum-features-based ANN-PSO approach for islanding detection in distribution system,” *IET Renewable Power Generation*, vol. 10, no. 9, pp. 1255–1263, 2016. doi: https://doi.org/10.1049/iet-rpg.2016.0080.

[53] F. Hashemi and M. Mohammadi, “Islanding detection approach with negligible non-detection zone based on feature extraction discrete wavelet transform and artificial neural network,” *International Transactions on Electrical Energy Systems*, vol. 26, no. 10, pp. 2172–2192, Oct. 2016. doi: https://doi.org/10.1002/etep.2197.

[54] S. A. Kumar *et al.*, “A novel islanding detection technique for a resilient photovoltaic-based distributed power generation system using a tunable-Q wavelet transform and an artificial neural network,” *Energies (Basel)*, vol. 13, no. 6, 4238, Aug. 2020. doi: https://doi.org/10.3390/en13164238.

[55] T. S. Menezes, D. v Coury, and R. A. S. Fernandes, “Islanding Detection Based on Artificial Neural Network and S-transform for Distributed Generators,” 2019. doi: https://doi.org/10.1109/PTC.2019.8810668.

[56] S. Admasie, S. B. A. Bukhari, T. Gush, R. Haider, and C. H. Kim, “Intelligent Islanding Detection of Multi-distributed Generation Using Artificial Neural Network Based on Intrinsic Mode Function Feature,” *Journal of Modern Power Systems and Clean Energy*, vol. 8, no. 3, pp. 511–520, May 2020. doi: https://doi.org/10.35833/MPCE.2019.000255.

[57] A. Khamis, H. Shareef, A. Mohamed, and E. Bizkevelci, “Islanding detection in a distributed generation integrated power system using phase space technique and probabilistic neural network,” *Neurocomputing*, vol. 148, pp. 587–599, Jan. 2015. doi: https://doi.org/10.1016/j.neucom.2014.07.004.

[58] M. Ahmadipour, H. Hizam, M. L. Othman, and M. A. M. Radzi, “An anti-islanding protection technique using a wavelet packet transform and a probabilistic neural network,” *Energies (Basel)*, vol. 11, no. 10, 2018. doi: https://doi.org/10.3390/en11102701.

[59] A. Masoud, B. M. Giyoev, and H. Hashim, “A New Islanding Detection Scheme Based on Combination of Slantlet Transform and Probabilistic Neural Network for Grid-Tied Photovoltaic System,” in *2019 International Youth Conference on Radio Electronics, Electrical and Power Engineering (REEPE)*, May 2019, pp. 1–6. doi: https://doi.org/10.1109/REEPE.2019.8708802.

[60] A. Hussain, C. H. Kim, and A. Mehdi, “A Comprehensive Review of Intelligent Islanding Schemes and Feature Selection Techniques for Distributed Generation System,” *IEEE Access*, vol. 9. Institute of Electrical and Electronics Engineers Inc., pp. 146603–146624, 2021. doi: https://doi.org/10.1109/ACCESS.2021.3123382.

[61] S. Li, A. J. Rodolakis, K. El-Arroudi, and G. Joós, “Islanding protection of multiple distributed resources under adverse islanding conditions,” *IET Generation, Transmission and Distribution*, vol. 10, no. 8, pp. 1901–1912, May 2016. doi: https://doi.org/10.1049/iet-gtd.2015.1105.

[62] R. Azim, F. Li, Y. Xue, M. Starke, and H. Wang, “An islanding detection methodology combining decision trees and Sandia frequency shift for inverter-based distributed generations,” *IET Generation, Transmission and Distribution*, vol. 11, no. 16, pp. 4104–4113, Nov. 2017. doi: https://doi.org/10.1049/iet-gtd.2016.1617.

[63] Q. Cui, K. El-Arroudi, and G. Joós, "Real-time hardware-in-the-loop simulation for islanding detection schemes in hybrid distributed generation systems," *IET Generation, Transmission and Distribution*, vol. 11, no. 12, pp. 3050–3056, Aug. 2017. doi: https://doi.org/10.1049/iet-gtd.2016.1562.

[64] S. Chandak, M. Mishra, and P. K. Rout, "Hybrid islanding detection with optimum feature selection and minimum NDZ," *International Transactions on Electrical Energy Systems*, vol. 28, no. 10, e2602, Oct. 2018. doi: https://doi.org/10.1002/etep.2602.

[65] C. R. Aguiar, G. Fuzato, R. F. Bastos, A. F. Q. Gonçalves, and R. Q. Machado, "Hybrid fuzzy anti-islanding for grid-connected and islanding operation in distributed generation systems," *IET Power Electronics*, vol. 9, no. 3, pp. 512–518, Mar. 2016. doi: https://doi.org/10.1049/iet-pel.2014.0717.

[66] S. D. Kermany, M. Joorabian, S. Deilami, and M. A. S. Masoum, "Hybrid Islanding Detection in Microgrid with Multiple Connection Points to Smart Grids Using Fuzzy-Neural Network," *IEEE Transactions on Power Systems*, vol. 32, no. 4, pp. 2640–2651, Jul. 2017. doi: https://doi.org/10.1109/TPWRS.2016.2617344.

[67] H. R. Baghaee, D. Mlakic, S. Nikolovski, and T. Dragicevic, "Support Vector Machine-Based Islanding and Grid Fault Detection in Active Distribution Networks," *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 8, no. 3, pp. 2385–2403, Sep. 2020. doi: https://doi.org/10.1109/JESTPE.2019.2916621.

[68] D. Mlakic, H. R. Baghaee, and S. Nikolovski, "A Novel ANFIS-Based Islanding Detection for Inverter-Interfaced Microgrids," *IEEE Transactions on Smart Grid*, vol. 10, no. 4, pp. 4411–4424, Jul. 2019. doi: https://doi.org/10.1109/TSG.2018.2859360.

[69] J. Y. Cheng, S. J. Huang, and C. T. Hsieh, "Application of Gabor-Wigner transform to inspect high-impedance fault-generated signals," *International Journal of Electrical Power and Energy Systems*, vol. 73, pp. 192–199, Dec. 2015. doi: https://doi.org/10.1016/j.ijepes.2015.05.010.

[70] M. Szmajda, K. Górecki, and J. Mroczka, "Gabor transform, Gabor-Wigner transform and SPWVD as a time-frequency analysis of power quality," 2010. doi: https://doi.org/10.1109/ICHQP.2010.5625371.

[71] T. P. Zielinski, "Joint Time-Frequency Resolution of Signal Analysis using Gabor Transform." *IEEE Transactions on Instrumentation and Measurement* 50.5, 1436-1444, 2001.

[72] S. Qian and D. Chen, “Discrete Gabor Transform,” in *IEEE transactions on signal processing*, 1993, vol. 41, no. 7. doi: 10.1109/78.224251.

[73] A. Hirofumi, W. Edson, and A. Mauricio, *instantaneous power theory and applications to power conditioning*. IEEE, 2017. doi: https://doi.org/10.1002/9781119307181.

[74] A. V. Dorogush, V. Ershov, and A. Gulin, “CatBoost: gradient boosting with categorical features support,” Retrieved Oct. 2018, from http://arxiv.org/abs/1810.11363

[75] K. M. Ghori, R. A. Abbasi, M. Awais, M. Imran, A. Ullah, and L. Szathmary, “Performance Analysis of Different Types of Machine Learning Classifiers for Non-Technical Loss Detection,” *IEEE Access*, vol. 8, pp. 16033–16048, 2020. doi: https://doi.org/10.1109/ACCESS.2019.2962510.

[76] M. M. Muhammed, A. A. Ibrahim, R. L. Ridwan, R. O. Abdulaziz, and G. A. Saheed, “Comparison of the CatBoost Classifier with other Machine Learning Methods,” Retrieved Dec 2020, From https://www.researchgate.net/publication/348277609

[77] F. Hashemi and M. Mohammadi, “Islanding detection approach with negligible non-detection zone based on feature extraction discrete wavelet transform and artificial neural network,” *International Transactions on Electrical Energy Systems*, vol. 26, no. 10, pp. 2172–2192, Oct. 2016. doi: https://doi.org/10.1002/etep.2197.

[78] J. A. Laghari, H. Mokhlis, M. Karimi, A. H. A. Bakar, and A. Shahriari, “Artificial Neural Network based Islanding Detection Technique for Mini hydro type distributed generation,” 2014.

[79] M. Pal, “Random forest classifier for remote sensing classification,” *International Journal of Remote Sensing*, vol. 26, no. 1, pp. 217–222, Jan. 2005. doi: https://doi.org/10.1080/01431160412331269698.

[80] S. Mishra, R. K. Mallick, D. A. Gadanayak, and P. Nayak, “A novel hybrid downsampling and optimized random forest approach for islanding detection and non-islanding power quality events classification in distributed generation integrated system,” *IET Renewable Power Generation*, vol. 15, no. 8, pp. 1662–1677, Jun. 2021. doi: https://doi.org/10.1049/rpg2.12137.

[81] A. Sanchay and B. Bhavesh R., “Islanding detection of distributed generation using random forest technique,” in *2016 IEEE 6th International Conference on Power Systems (ICPS)*, 2016, pp. 1–6. doi: https://doi.org/10.1109/ICPES.2016.7584192.

[82] A. G. Abd-Elkader, D. F. Allam, and E. Tageldin, “Islanding detection method for DFIG wind turbines using artificial neural networks,” *International Journal of Electrical Power and Energy Systems*, vol. 62, pp. 335–343, 2014. doi: https://doi.org/10.1016/j.ijepes.2014.04.052.

[83] A. Khamis, H. Shareef, and A. Mohamed, “Islanding detection and load shedding scheme for radial distribution systems integrated with dispersed generations,” *IET Generation, Transmission and Distribution*, vol. 9, no. 15, pp. 2261–2275, Nov. 2015. doi: https://doi.org/10.1049/iet-gtd.2015.0263.

UAEU جامعة الإمارات العربية المتحدة United Arab Emirates University

UAE UNIVERSITY MASTER THESIS NO. 2022: 44

The research context perspectives develop a reliable intellegent algorithm for a protection device in power system called relay, while protecting the power system from operating in island mode. Therefore, alot of researches related to this challenge were developed and implemented to construct an intellegent algorithms to detect the various disturbances in power system.

Mohannad Suleiman received his Master of Science in Electrical and Communication Engineering from the Department of Electrical and Communication Engineering, College of Engineering at UAE University, UAE. He received his BSc from the college of Electrical Engineering, Polytechnic University, Jordan.

www.uaeu.ac.ae

Online publication of thesis:

https://scholarworks.uaeu.ac.ae/etds/